

CENTRAL INSTITUTE OF
EDUCATION, DELHI
LIBRARY

Call No. ... ~~312.3384~~

Book No. ... ~~E 425, E.~~

SELECTED
TECHNIQUES OF
STATISTICAL ANALYSIS

for Scientific and Industrial Research
and
Production and Management Engineering)

BY THE
STATISTICAL RESEARCH GROUP, COLUMBIA UNIVERSITY

APPLIED MATHEMATICS PANEL, OFFICE OF SCIENTIFIC
RESEARCH AND DEVELOPMENT

EDITED BY
CHURCHILL EISENHART, National Bureau of Standards
MILLARD W. HASTAY, National Bureau of Economic Research
W. ALLEN WALLIS, University of Chicago

New York and London
McGRAW-HILL BOOK COMPANY, Inc.
1947

TECHNIQUES OF STATISTICAL ANALYSIS

COPYRIGHT, 1947, BY THE
MCGRAW-HILL BOOK COMPANY, INC.

PRINTED IN THE UNITED STATES OF AMERICA

*All rights reserved. This book, or
parts thereof, may not be reproduced
in any form without permission of,
the publishers.*

THE MAPLE PRESS COMPANY, YORK, PA.

TO
WARREN WEAVER

PREFACE

SPONSORSHIP OF THE WORK

This volume was prepared by the Statistical Research Group, Division of War Research, Columbia University, for the Applied Mathematics Panel, National Defense Research Committee, Office of Scientific Research and Development. The work was initiated under contract OEMsr-618 and completed under contract OEMsr-1131, both between the Trustees of Columbia University and the Office of Scientific Research and Development. Royalties, at usual rates, are being paid by the publisher to the United States government; no royalties are being paid to Columbia University or to any private institution or individual. The publisher has agreed that ten years after the date on which this volume is issued the copyright thereon shall be relinquished and the work shall become part of the public domain.

The Statistical Research Group was organized and its initial staff selected by Warren Weaver, Chief of the Applied Mathematics Panel, on July 1, 1942. The staff was drawn from universities and research organizations throughout the country, many of which generously granted leaves for the work. The group disbanded September 30, 1945, except for a few persons who have prepared this and another volume as monographs in connection with the Applied Mathematics Panel's Summary Technical Report.

NATURE OF THE BOOK

This book discusses a series of problems that occur frequently in planning, analyzing, or interpreting quantitative data. Various techniques appropriate to these problems are explained, in terms of both general principles and specific procedures.

The book is written for scientists, engineers, managers, and statisticians. It seeks to explain the statistical approach to various problems, to expound the theory that can be brought to bear on each problem, to point out the features of the problem that determine the relevance of the theory, to give detailed and workable computational procedures, including formulas, tables, and charts, and to illustrate the interpretation of the results. Concrete illustrative material is used to bring out the interplay of substantive and statistical considerations, the illustrations being selected primarily for the light they throw on the art of applying statistical techniques and only secondarily for intrinsic interest. Although relatively little new statistical theory is included, several topics are given more thoroughly integrated and carefully expounded treatment than has previously been available, and many new tables are included.

In preparing this book, the authors have kept in mind the reader who is interested in applying statistical techniques in his work but who either does not have much interest in or time for studying general statistical theory as such, or else feels that he can best understand and appreciate statistical theory through a series of special problems. Even the statistical theorist, however, should be able to deepen and broaden his understanding and appreciation of statistical theory by examining special problems in some detail.

The chemical, physical, and engineering sciences are, on the whole, distinctly backward in the statistical planning of experiments and the analysis of empirical data, at least by comparison with the social, biological, and agricultural sciences. No doubt this is partly because physical scientists have attained a high degree of proficiency in experimental techniques and can make repeated, independent experimental investigations of a given phenomenon—they can “think with their hands”—so that competent investigators are likely to learn the truth (though perhaps belatedly and at excessive cost) despite crudities in statistical techniques. In the social and biological sciences, on the other hand, repetition or control of experimental procedures is usually impossible, at least in anything like the degree achieved in the physical sciences, so that the truth can be learned only through highly developed statistical techniques closely coupled (as statistical techniques must always be) with sound scientific knowledge and techniques. But even though sound statistical techniques may not be indispensable in the physical sciences, they are invaluable. Increasing recognition of this, accelerated by developments during the war, is leading to the rapid introduction of statistical methods into chemistry, physics, and engineering; indeed, it seems likely that in the immediate future the greatest contributions of statistics will be to, and its greatest developments will arise from, the physical sciences. (The physical sciences may, however, yield this distinction to medicine, which is said to be nearly as dependent on statistics as the social sciences and nearly as backward statistically as the physical sciences.)

BACKGROUND

During the war the Statistical Research Group carried on three kinds of work: (1) It advised and assisted the Army, the Navy, and the Office of Scientific Research and Development on the statistical aspects of problems arising in their activities; this constituted the largest part of the work. (2) It assumed primary responsibility for the investigation of certain problems of a predominantly statistical or probabilistic character. (3) It developed, reviewed, or expounded statistical techniques; this was the smallest part of the work and was incidental to the first two.

The great bulk of the work fell into the first two categories, and the final products did not emphasize statistical techniques as such. From this work, however, there arose a number of developments in applied statistics, as well as some in theoretical statistics. This book has been prepared to preserve and to disseminate useful statistical material that was almost a by-product of the responsible and cooperative handling of practical military, scientific, engineering, and production problems.

AUTHORSHIP

Because it would be difficult or impossible accurately to assign personal credit and responsibility for this volume, its authorship is attributed to the Statistical Research Group as a whole. Under ordinary circumstances the basic material of the various chapters would have been published in technical journals by the originators individually. Under the actual circumstances, many ideas are presented here for the first time in chapters prepared by others than those who did the basic work. It thus becomes important to assign credit for the ideas in such chapters without at the same time implying responsibility for the entire content or emphasis. An attempt has been made to do this by notes at the beginning of the chapters. The editors, and in particular the undersigned, however, have exercised final judgment and authority over the form and content of each chapter and are thus in the unhappy position of having to assume all responsibility for the shortcomings of the book without being able to claim credit for its merits.

The following were members of the senior scientific staff of the Statistical Research Group, and the influence of each is reflected in the book.

Kenneth J. Arnold, *University of Wisconsin*
 Rollin F. Bennett, *Columbia University*
 Julian H. Bigelow, *Institute for Advanced Study*
 Albert H. Bowker, *Stanford University*
 Churchill Eisenhart, *National Bureau of Standards*
 (on leave from *University of Wisconsin*)
 H. A. Freeman, *Massachusetts Institute of Technology*
 Milton Friedman, *University of Chicago*
 M. A. Girshick, *U. S. Bureau of the Census*
 Millard W. Hastay, *National Bureau of Economic Research*
 Harold Hotelling, *University of North Carolina*
 Edward Paulson, *University of North Carolina*
 L. J. Savage, *University of Chicago*
 Herbert Solomon, *Stanford University*
 George J. Stigler, *Brown University*
 A. Wald, *Columbia University*
 W. Allen Wallis, *University of Chicago*
 J. Wolfowitz, *Columbia University*

Of the junior scientific staff, those whose work has especially affected this volume include Nancy Brixey Breen, Henry Goldberg, Anne Frankenthaler Kohn, Harriet Levine, and Myra Levine.

ACKNOWLEDGMENTS

A large share of any credit for the work of the Statistical Research Group must be assigned to Warren Weaver, Chief of the Applied Mathematics Panel, for his rare talents in administering research; he succeeded on the one hand in providing the information, guidance, and evaluation necessary to steer the work into channels effectively furthering the objectives of the Office of Scientific Research and Development and, on the other hand, in allowing the wide range of individual freedom, initiative, and responsibility that is vital to research.

Preparation and publication of this volume would probably have been impossible, and certainly would have been most difficult, without the indefatigable, efficient, and unstinting assistance of Mina Rees of the Applied Mathematics Panel. George B. Pegram, Chairman of the Columbia University Committee on War Research, gave encouragement and material assistance that was important in launching and carrying through the project to prepare this volume.

On nearly every chapter Kenneth J. Arnold gave the editors advice and assistance, which eliminated a number of errors and in many cases introduced substantial improvements.

Special efforts have been made to insure the accuracy of reference tables. Through the courtesy of the National Bureau of Standards, proofs of Tables 2.1, 8.1, 8.2, 8.3, 8.4, 15.1, and 15.2 were checked by the New York Mathematical Tables Project directed by Arnold N. Lowan; the printed tables were tested by differencing or, when necessary, by recomputation or other means. Proofs of Tables 1.1, 1.5, 14.1, and 16.4 were compared with published tables not used in their preparation.

The index was prepared by Churchill Eisenhart, assisted by Celia S. Martin. Edythe B. Rodermund prepared and, insofar as time permitted, edited the typescript with extraordinary diligence, accuracy, and thoroughness. The charts (except Figs. 10.1 and 10.2) are the work of H. Irving Forman.

W. ALLEN WALLIS
Director of Research
Statistical Research Group

CHICAGO, ILL.,
January, 1947.

CONTENTS*

PREFACE.	vii
LIST OF REFERENCE TABLES.	xiii

PART I. INDUSTRIAL STATISTICS

1. Use of Variables in Acceptance Inspection for Percent Defective.	3
<i>W. ALLEN WALLIS, University of Chicago</i>	
2. Tolerance Limits for Normal Distributions.	95
<i>ALBERT H. BOWKER, Stanford University</i>	
3. Multivariate Quality Control Illustrated by the Air Testing of Sample Bombsights.	111
<i>HAROLD HOTELLING, University of North Carolina</i>	
4. Effects of Rounding or Grouping Data	185
<i>CHURCHILL EISENHART, National Bureau of Standards</i>	
5. Acceptance Inspection When Lot Quality Is Measured by the Range	225
THE EDITORS, based on work by <i>M. A. Girshick, U. S. Bureau of the Census</i>	
6. Variability of Amount of Inspection for Double, Multiple, and Sequential Sampling.	235
THE EDITORS, based on work by <i>Myra Levine, Socony-Vacuum Oil Company</i>	

PART II. PLANNING EXPERIMENTS

7. Planning and Analyzing Experiments for Comparing Two Percentages.	247
<i>EDWARD PAULSON, University of North Carolina</i> <i>W. ALLEN WALLIS, University of Chicago</i>	
8. Planning and Interpreting Experiments for Comparing Two Standard Deviations.	267
<i>CHURCHILL EISENHART, National Bureau of Standards</i>	
9. Utilization of Limited Experimental Facilities When the Cost of Each Measurement Depends on Its Magnitude	319
<i>MILTON FRIEDMAN, University of Chicago</i>	
10. Experiments in Which the Independent Variable Is Known Only in Terms of a Probability Distribution.	329
THE EDITORS, based on work by <i>J. Wolfowitz, Columbia University</i>	
11. Planning an Experiment for Estimating the Mean and Standard Deviation of a Normal Distribution from Observations on the Cumulative Distribution	339
<i>MILTON FRIEDMAN, University of Chicago</i>	

* An analytical table of contents appears at the beginning of each chapter.

LIST OF REFERENCE CHARTS

5.1 Cumulative Probability Distribution of the Range in Samples of k from a Normal Population.	230
7.1 Number of Cases Required for Comparing Two Percentages.	260
8.1 Operating-characteristic Curves for Experiments to Determine Whether a New Product (Process) Is More Variable Than a Standard Product (Process) of Known Variability, 0.05 Level of Significance.	274
8.2 Operating-characteristic Curves for Experiments to Determine Whether a New Product (Process) is More Variable than a Standard Product (Process) of Known Variability, 0.01 Level of Significance.	275
8.3 Operating-characteristic Curves for Experiments to Determine Whether a Particular One of Two New Products (Processes) Is More Variable Than the Other, 0.05 Level of Significance.	296
8.4 Operating-characteristic Curves for Experiments to Determine Whether a Particular One of Two New Products (Processes) Is More Variable Than the Other, 0.01 Level of Significance.	297
10.1 Ninety-nine Percent Confidence Belts for Population Proportion . .	332
10.2 Ninety-five Percent Confidence Belts for Population Proportion . .	333
10.3 Ninety Percent Confidence Belts for Population Proportion	334
10.4 Eighty Percent Confidence Belts for Population Proportion	335
14.1 Probability That Means of Samples from Two Normal Populations Will Be in Opposite Order to Population Means	379

Part I
INDUSTRIAL STATISTICS

	Page
Chapter 1. Use of Variables in Acceptance Inspection for Percent Defective	3
Chapter 2. Tolerance Limits for Normal Distributions	95
Chapter 3. Multivariate Quality Control, Illustrated by the Air Testing of Sample Bombsights	111
Chapter 4. Effects of Rounding or Grouping Data	185
Chapter 5. Acceptance Inspection When Lot Quality Is Measured by the Range	225
Chapter 6. Variability of Amount of Inspection for Double, Multiple, and Sequential Sampling	235

CHAPTER 1

USE OF VARIABLES IN ACCEPTANCE INSPECTION FOR PERCENT DEFECTIVE

	Page
1. Attributes and Variables	7
2. Background of the Plan	9
3. Three Phases of a Variables Sampling Plan.	13
3.1 The Three Phases	13
3.2 Plan of Action.	14
3.3 Amount of Inspection	14
3.4 Operating Characteristics (OC)	15
4. Plan of Action	16
4.1 General Procedure.	16
4.2 Formulas for k and N	17
4.3 Illustration	18
4.4 Adjustment of N	19
4.5 Adjustment of k with N Fixed.	19
4.5.1 Formula.	19
4.5.2 Example.	20
4.5.3 A Special Case: Indifference Quality.	20
4.6 Approximations in the Plan.	21
4.7 Table of N and k	21
5. Amount of Inspection	26
5.1 Comparison with Attribute Inspection	26
5.2 Comparison with Variables Inspection When the Standard Deviation Is Known.	27
6. Operating-characteristic Curve	28
6.1 Introduction.	28
6.2 Five-point OC Curve.	28
6.3 Detailed OC Curve.	30
6.3.1 Illustrative Computation for One Point	30
6.3.2 Work Sheet for Detailed OC Curve.	32
7. Techniques of Applying the Plan	33
7.1 Introduction.	33
7.2 Computational Procedure.	34
7.2.1 Formulas	34
7.2.2 Example.	35
7.3 Graphical Procedure.	36
7.3.1 Original Data	36
7.3.2 Adjusted Data	36
8. Reduced and Tightened Inspection	41
8.1 Purpose of Reducing or Tightening Inspection.	41
8.2 Criteria for Reducing or Tightening Inspection	42
8.2.1 Process Average Percent Defective	42

	PAGE
8.2.2 Illustrative Computation of Process Average	44
8.3 Methods of Reducing or Tightening Inspection	45
9. Choice of Quality Standards and Evaluation of Proposed Sampling Plans	45
9.1 General Discussion.	45
9.2 Analysis of Production Possibilities.	46
9.3 Analysis of Consumption Requirements	47
9.4 Normality Assumption	49
10. Simultaneous Use of Several Sampling Plans	50
10.1 Inspection of Several Quality Characteristics.	50
10.2 Upper and Lower Bounds on a Single Quality Characteristic	52
10.2.1 General Considerations	52
10.2.2 Use of a Pair of One-sided Criteria	53
10.2.3 Two-sided Criterion.	54
11. Technical Notes.	57
11.1 Basic Formulas.	57
11.1.1 Assumptions.	57
11.1.2 Direct Derivation	59
11.1.3 Derivation from General Formulas for Sample Size and Critical Level.	61
11.1.4 Two-sided Criterion.	63
11.2 Approximations in the Basic Formulas	64
11.3 Computational Formulas.	66
11.4 Use of Non-central t Distribution	71
11.4.1 Introduction.	71
11.4.2 Notation Used in the Tables.	72
11.4.3 Description of the Tables	73
11.4.4 Calculation of $\delta(f, t_0, e)$	74
11.4.5 Calculation of $t(f, \delta, e)$	75
11.4.6 Illustration of the Use of the Non-central t Tables in Specific Problems	76
11.4.7 Work Sheets.	77
11.5 Construction of Table 1.2	81
11.6 Sequential Analysis of Proportion Defective by Variables	83
12. Notation.	85
13. References	93

FIGURES

1.1 Normal Distribution.	10
1.2 Combinations of μ and σ Corresponding with the Same Percent Defective	11
1.3 Typical Operating-characteristic (OC) Curve	15
1.4 Operating-characteristic (OC) Curve for a Variables Inspection Plan for Percent Defective; $N = 95$, $k = 0.7645$	29
1.5 Graphical Procedure for Determining from Σx and Σx^2 Whether $\bar{x} + ks \leq U$; $N = 95$, $k = 0.7645$, $U = 35$	38
1.6 Enlarged Segment of Computational Chart in Terms of Original Data (Enlargement of Area Indicated in Fig. 1.5).	39
1.7 Graphical Procedure for Determining from Σx and $\Sigma(x - A)^2$ Whether $\bar{x} + ks \leq U$; $N = 95$, $k = 0.7645$, $U = 35$, $A = 30$	40
1.8 Acceptance Region for a Two-sided Test Defined by $p_1 = 0.15$, $p_2 = 0.30$, $\alpha = 0.01$, $\beta = 0.02$, $U = 35$, $M = 25$, and Corresponding Region for a Pair of One-sided Tests.	55

TABLES

	PAGE
1.1 Normal Deviates Exceeded with Given Probability	18
1.2 Values of N and k for Various Combinations of p_1 and p_2 when $\alpha = 0.05$ and $\beta = 0.10$	22
1.3 Sample Sizes for Eight Pairs of Single-sampling Plans Based on Attributes and Variables	26
1.4 Sample Sizes for Eight Pairs of Single-sampling Variables Plans Based on Known and Unknown Standard Deviations	27
1.5 Probabilities Corresponding with Given Normal Deviates	31
1.6 Work Sheet for Operating-characteristic Curve.	32
1.7 Computation of Boundary of Acceptance Region for a Two-sided Test Defined by $p_1 = 0.15$, $p_2 = 0.30$, $\alpha = 0.01$, $\beta = 0.02$, $U = 35$, $M = 25$	56
1.8 Comparison of Approximate and Exact Values of N and k	65
1.9 Work Sheet 1 for Determining u_α (in Our Notation k) from Non-central t Tables	77
1.10 Work Sheet 2 for Determining u_α —Computation of $t(f, \delta, c)$	78
1.11 Work Sheet 3 for Determining u_α —Linear Interpolation for $\lambda(a, b)$	79
1.12 Work Sheet 4 for Operating-characteristic Curve.	80

This chapter was prepared by
W. Allen Wallis, University of Chicago

Secs. 11.4, 11.5, and 12 were drafted by Harriet Levine. The material of Secs. 10.2.3 and 11.1.4 is due to Kenneth J. Arnold. The comparison made in Sec. 5.2 was suggested by Milton Friedman. The general character of the Statistical Research Group's work on inspection by variables was greatly influenced by M. A. Girshick, who had direct charge of the work in which this type of inspection was most used.

CHAPTER 1

USE OF VARIABLES IN ACCEPTANCE INSPECTION FOR PERCENT DEFECTIVE

1. ATTRIBUTES AND VARIABLES

Acceptance inspection is the process of judging whether a lot of items is of acceptable quality by examining a sample from the lot. Such inspection is widely and successfully used in industry. It is usually carried out by classifying each item in the sample as either defective or nondefective, then deciding from the number of defective items in the sample whether the percentage of defective items in the lot is small enough for the lot to be considered acceptable. Thus, the quality of the lot is measured by the percentage of defective items, and this is judged by classifying the sample items according to attributes.

Often the sample items are classified as defective or nondefective on the basis of a measurable quality characteristic. For example, the items may be classified as too heavy or not, although the actual weight could be measured; they may be classified as too short or not, although the length could be measured; they may be classified as having an excessive volatile content or not, although the volatile content could be measured; they may be classified as operating too fast or not, although the speed could be measured; they may be classified as having too short a useful life or not, although the useful life could be measured. Such cases, where inspection is based on attributes, may be contrasted with cases in which inspection is based on variables, that is, on the actual measured values of the characteristic.

Inspection by variables has one major advantage over inspection by attributes: fewer items need be inspected for a given degree of accuracy in judging a lot's acceptability; or, conversely, decisions about the lot are more reliable if based on a sample inspected by variables than if based on a sample of the same size inspected by attributes. The reason for this is that variables inspection provides more information about the quality of each item; for example, that the volatile content is 16.02 percent or 20.61 percent, as the case may be, instead of merely that the volatile content exceeds, say, 16 percent in both cases. Since variables inspection provides more information about each item, a smaller number of sample items gives the same amount of information about the lot, or the same number of sample items gives more information about the lot.

The principal advantage of inspection by attributes over inspection by variables is that it requires less skill, less time, or less expensive equipment to inspect each item; less record-keeping to record the results of inspection; less arithmetic to determine from the sample results whether the lot should be judged acceptable. Usually this advantage of simplicity more than offsets the fact that more items must be inspected under attribute than under variables inspection.

Another advantage of attribute inspection is that the selection and installation of sound sampling plans is easier. In fact, complete and detailed procedures are available in such form that little or no previous knowledge of technical statistics is required for their successful use.* In attribute inspection the mathematical theory about the manner in which quality varies from one item to another is always fulfilled if the sample is selected at random from the lot. The mathematical theory underlying variables inspection plans, on the other hand, is that quality varies among the items of the lot in accordance with a normal (Gaussian) distribution; whether this theory is a sufficiently good approximation to the facts in a particular inspection problem is a matter requiring investigation by statistical methods.

There are other less important reasons for preferring attributes to variables. One of these is a misapprehension as to the amount of arithmetic required, often based in large part on ignorance of short-cut computational procedures. Another such reason is exaggeration of the limitations imposed by the normality assumption in the mathematics underlying variables inspection.

Attributes are sometimes used instead of variables because well-known sampling plans for variables measure lot quality by the average or the variability of the measurements, while well-known attribute plans measure it by the percent defective. Percent defective is often the appropriate measure, and its appropriateness is not affected by shifting between attributes and variables. For example, in inspecting rods for length, the percent too short may in some circumstances be a better measure of quality than either the mean or the variability of length—as when rods below a certain length are useless while those above that length can easily be trimmed at virtually no extra cost. Similarly, in determining whether individual packages in a lot provide full measure, the percent below the specified measure may be more significant than the average measure. Variables plans for percent defective exist but are not widely known.†

* See, for example, Statistical Research Group, *Sampling Inspection*; Dodge and Romig, *Sampling Inspection Tables* (for full citations see Sec. 13).

† See especially the following two papers, of which this chapter is primarily a development: JENNETT and WELCH, "The Control of Proportion Defective"; JOHNSON and WELCH, "Applications of the Non-central t Distribution."

Although in most cases attribute plans are undoubtedly more economical than variables plans for percent defective, because the lower cost of inspecting each item usually more than offsets the increase in the number of items that must be inspected, variables inspection offers decided advantages in far more instances than has usually been recognized. This is especially true when the inspection process is costly, as for example when it requires expensive time, equipment, or personnel, or when the items are expensive and are damaged or destroyed by inspection. It is also true when measurement by variables costs only a little more than classification by attributes, or when for purposes other than acceptance inspection the data on variables are more valuable than those on attributes. Thus it is desirable that the practical aspects of variables plans be more fully developed and the plans made more generally available than has heretofore been the case.

2. BACKGROUND OF THE PLAN

A variables plan of acceptance inspection for percent defective is based upon the sample mean and the sample standard deviation. Other measures of central tendency and variability could be used, for example, the median and the range. No other measures are considered in this chapter, however, because other measures all require larger samples to give as good results as the mean and standard deviation. The gains in computational simplicity that may be afforded by other measures are likely to be unimportant in the situations for which variables inspection is appropriate. Although in routine inspection operations it is not necessary to compute either the mean or the standard deviation, it will clarify the ideas to begin the discussion in terms of them.

A normal distribution, such as that shown in Fig. 1.1, is characterized by two quantities (parameters), its mean μ and its standard deviation σ . Normal distributions have large or small means according as μ is large or small; the observations are tightly clustered or widely scattered about the mean according as σ is small or large. The proportion of the observations exceeding a certain upper limit, say U , depends upon how far the limit is above the mean, measured in terms of the standard deviation. For example, if the limit exceeds the mean by twice the standard deviation, that is, if $U = \mu + 2\sigma$, 2.275 percent of the observations exceed the limit; but if the limit exceeds the mean by three times the standard deviation, that is, if $U = \mu + 3\sigma$, only 0.135 percent of the observations exceed the limit. To determine the percent of observations exceeding any limit, first subtract the mean from the limit and then divide the difference by the standard deviation; that is, compute

$$K = \frac{U - \mu}{\sigma} \quad (1)$$

which shows the difference between the limit and the mean as a multiple of the standard deviation. Various tables show for different values of K what part of a normal distribution exceeds K .*

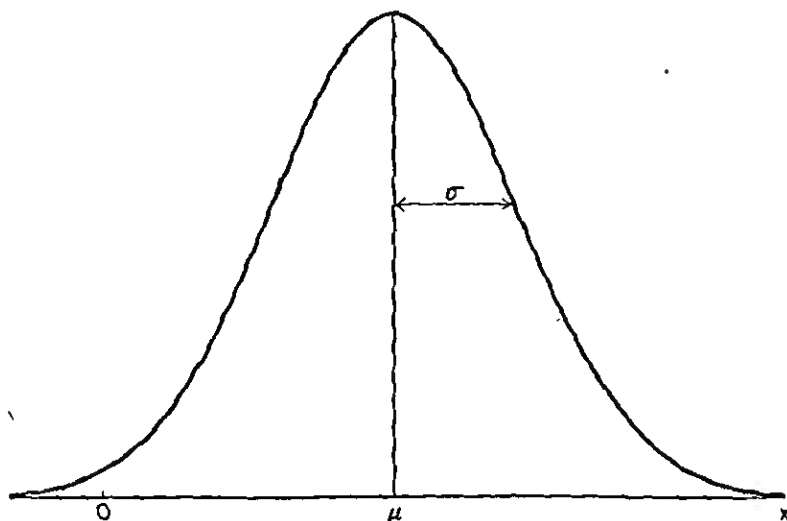


FIG. 1.1.—Normal distribution.

From formula (1) it is clear that the proportion exceeding a given limit U , which we will call the fraction defective, depends upon both the mean and the standard deviation. For a given standard deviation, the fraction defective is smaller the smaller the mean; but, however small the mean, the standard deviation may be large enough to cause a high

* See, for example, Table 1.1 in this chapter. By far the most extensive table is that prepared by the New York Mathematical Tables Project, *Tables of Probability Functions*. This gives probabilities to 15 decimal places for values of K (denoted by x in the tables) from 0 to 1 by steps of 0.0001, and for all values of K above 1 by steps of 0.001.

Some care is required in using tables of the normal probability function, since two different kinds of table are common and several methods of tabulation are used. The two kinds of table differ in the units used to measure the difference between the limit and the mean, the most common type (illustrated by Vol. II of the NYMTP tables) measuring this as a multiple of the standard deviation and the other type (illustrated by Vol. I of the NYMTP tables) measuring it as a multiple of $\sqrt{2}$ times the standard deviation. Thus, to enter the second type of table, K computed from formula (1) must be divided by $\sqrt{2} = 1.414$. In either type of table the entries may represent (a) the proportion exceeding K , which is the same as the proportion below $-K$; (b) the proportion below K , which is the same as the proportion above $-K$; (c) the proportion between the mean and K , which is the same as the proportion between the mean and $-K$; (d) the proportion between $-K$ and K ; (e) the proportion below $-K$ and above $+K$. Given any one of these five values, the others are easily computed from the facts that the distribution is symmetrical about the mean and that the total proportion is one.

fraction defective. For a fixed mean less than the limit, the fraction defective is smaller the smaller the standard deviation; but, however small the standard deviation, the mean may be large enough to cause a high fraction defective. The acceptability of any mean, when quality is measured by fraction defective, depends on the standard deviation; and the acceptability of any standard deviation depends on the mean.

Figure 1.2 illustrates various combinations of the mean and standard deviation that correspond to the same lot quality, as measured by fraction

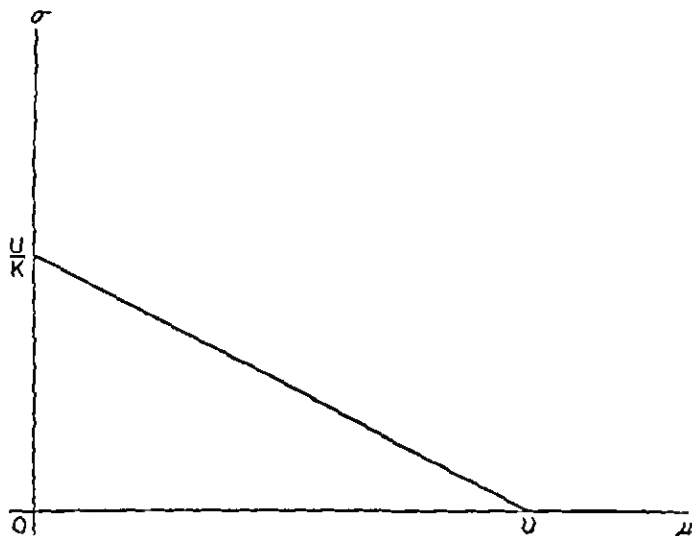


FIG. 1.2.—Combinations of μ and σ corresponding with the same percent defective.

defective. Any combination corresponding to a point on the sloping line represents the same quality; combinations to the left of the line represent better quality (lower fraction defective), those to the right worse quality. Any lot quality can be represented by such a line, the percent defective being greater the steeper the line.* Thus a lot is acceptable, in the sense that it has a fraction defective less than or equal to a specified acceptable quality level (AQL), whenever $(U - \mu)/\sigma$ is greater than or equal to a certain value of K which depends on the AQL, and can be determined from tables of the normal probability function. In other words, the lot is acceptable if its mean plus a certain multiple of its standard deviation does not exceed the limit; that is, if

$$\mu + K\sigma \leq U \quad (2)$$

* Lot qualities worse than 50 percent defective would be represented by a line starting at $\mu = U$, $\sigma = 0$ and sloping upward to the right. When the mean exceeds the limit the percent defective exceeds 50, and for a given mean the percent defective is smaller the larger the standard deviation. Such cases are rarely of interest in acceptance sampling but can be treated by formulas (1'), (2'), and (3') below.

The discussion so far has been entirely in terms of the lot mean and standard deviation. In practice, the lot mean and standard deviation, μ and σ , are unknown, and it is necessary to judge from the sample mean and standard deviation, \bar{x} and s , whether they satisfy criterion (2). This can be done by adding a multiple of the sample standard deviation to the sample mean and comparing the sum with the limit. In choosing the multiple of the sample standard deviation, however, allowance must be made for the fact that the mean and standard deviation determined from the sample are subject to fluctuations from sample to sample. That is, if a number of samples are drawn from lots having exactly the same fraction defective, the samples will not all yield the same value of $(U - \bar{x})/s$. Thus the acceptable level of $(U - \bar{x})/s$, say k , must be small enough so that there will not be too high a probability that an acceptable lot will fail to meet the acceptance criterion for the sample, namely,

$$\bar{x} + ks \leq U \quad (3)$$

If the sample contains measurements on N items (that is, contains N observations) represented by x_1, x_2, \dots, x_N , the sample mean \bar{x} is

$$\bar{x} = \frac{x_1 + x_2 + \dots + x_N}{N} = \frac{\sum x_i}{N} \quad (4)$$

the sample variance s^2 is

$$s^2 = \frac{(x_1 - \bar{x})^2 + (x_2 - \bar{x})^2 + \dots + (x_N - \bar{x})^2}{N - 1} = \frac{\sum (x_i - \bar{x})^2}{N - 1} \quad (5)$$

and the sample standard deviation s is the square root of the sample variance.

A few miscellaneous remarks will complete the background of variables inspection plans for percent defective:

The symbols μ and σ are used to indicate the population mean and standard deviation; \bar{x} and s are used to represent the sample mean and standard deviation. Similarly, K is used to represent the deviation of the lot mean from the limit in units of the lot standard deviation, and k is used to represent the deviation of the sample mean from the limit in units of the sample standard deviation. This is in conformity with the sound and increasingly prevalent practice of using notation that emphasizes the distinction between true lot (*population* or *universe*) parameters and sample estimates of these parameters—an estimate meaning in statistical usage a value calculated from a sample (not guessed or judged in the everyday sense of “estimate”) according to established principles for estimating lot parameters from sample data. Neglect of the distinction between lot parameters and sample estimates of them can be (and often is) a cause of serious confusion. The quantities \bar{x} and

s , which for brevity have been called the sample mean and standard deviation, should properly be called the sample estimates of the lot mean and standard deviation.

The use of $N - 1$ instead of N in the denominator of the variance [see formula (5)] has no real influence on the sampling plan provided the k of expression (3) is chosen with due regard to whether N or $N - 1$ is used. If N is used, the proper value of k is greater by a factor $\sqrt{N/(N - 1)}$ than if $N - 1$ is used, so k times s is the same in either case. If, however, the value of s is itself of interest, the use of $N - 1$ is preferable.

Although formula (5) is useful for bringing out the meaning of the standard deviation, it should not be used for computing purposes. For computing, use one of the following two forms:

$$s^2 = \frac{\sum x^2 - \frac{(\sum x)^2}{N}}{N - 1} \quad (6a)$$

$$= \frac{N \sum x^2 - (\sum x)^2}{N(N - 1)} \quad (6b)$$

For purposes of acceptance inspection, however, it is not necessary (as will be seen later) actually to compute the standard deviation.

For concreteness it is assumed that defective items are those for which the value of the quality characteristic exceeds some upper bound of satisfactory quality U . It would be equally appropriate to assume that defective items are those below some minimum M . In that case, equations (1), (2), and (3) would be

$$K = \frac{\mu - M}{\sigma} \quad (1')$$

$$\mu - K\sigma \geq M \quad (2')$$

$$\bar{x} - ks \geq M \quad (3')$$

In what follows, the assumption is retained that defectives are items that are too large, but from equations (1'), (2'), and (3') the application to cases where defectives are items that are too small will be obvious.

3. THREE PHASES OF A VARIABLES SAMPLING PLAN

3.1. The Three Phases

A sampling procedure may be analyzed into three phases:

(1) The *plan of action*, that is, the set of rules on the basis of which to accept or reject the lot.*

(2) The *amount of inspection* required by the plan, that is, the number of items that must be inspected from each lot.

* Some plans allow a third decision, to inspect more items; see Sec. 11.6.

(3) The *operating characteristics* of the plan, that is, the proportions of submitted lots of various qualities that will be accepted and rejected if the plan is used.

3.2. Plan of Action

The plan of action for variables inspection for percent defective is as follows:

- a. A sample of N items is selected at random from the lot.
- b. The quality characteristic being inspected is measured and recorded for each item of the sample.
- c. The mean and standard deviation are computed from the N measurements.
- d. The sample standard deviation is multiplied by a certain constant k and added to the sample mean.
- e. The lot is rejected if the value of $\bar{x} + ks$ found in step d exceeds U , the limit of the quality characteristic above which an item is considered defective; otherwise, the lot is accepted.

In practice, steps c and d can be replaced by a single step that consists essentially of adding the squared values of the N sample measurements; in that case step e remains essentially as stated, though the actual numbers used in it are different.

Thus, the plan of action is characterized by two parameters: the sample size N and the multiplier of the standard deviation k . (U is associated with the definition of quality rather than with the sampling plan, since it simply defines a defective item.)

3.3. Amount of Inspection

Under the plans considered here, which are single-sampling plans, the number of items inspected per lot is always the same for a given plan.

Single-sampling plans for fraction defective based on attributes can sometimes be curtailed, that is, terminated without inspecting all N items. Curtailing is possible as soon as the number of defectives reaches the rejection number or the number of defectives plus the number of items remaining to be inspected is less than the rejection number. Plans based on variables can also be curtailed, provided there is some minimum possible value of the characteristic being inspected. Most acceptance inspection involves quantities that can under no circumstances be less than zero, so curtailing before inspecting all N items is technically possible. The simplest example of this possibility is the case in which, with k positive, the sum of fewer than N measurements exceeds NU , making it clear that for the entire N items \bar{x} will exceed U and $\bar{x} + ks$ will exceed it still further. That there are other cases, less extreme but more complicated to describe, in which curtailing is possible can be seen by studying Sec. 11.3 below. Ordinarily, however, curtailing is not considered

because computations are not started until all measurements have been made. When it is possible to carry out simple computations while the data are being collected and it is important to minimize the amount of inspection, sequential analysis of the data will be considerably more efficient than merely curtailing a single-sampling plan. A brief outline of a plan for sequential analysis of fraction defective by variables is presented in Sec. 11.6.

3.4. Operating Characteristics (OC)

There are evidently many possible plans of action, for each different combination of sample size and multiplier of the standard deviation

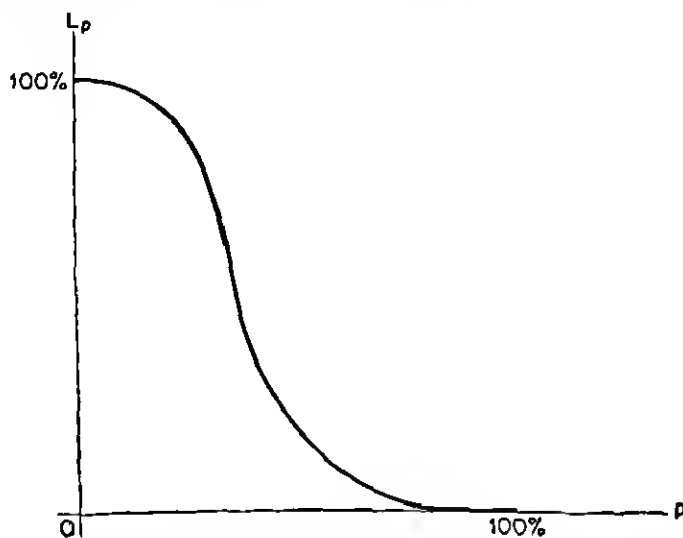


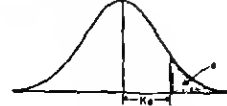
FIG. 1.3.—Typical operating-characteristic (OC) curve.

gives a different plan of action. If a large number of lots containing a given fraction defective p are submitted to a given plan, a certain proportion L_p are accepted; and this proportion differs from one plan to another. For each plan of action, it is important to know what proportion of submitted lots will be accepted for each possible quality p of submitted lots, as a plan is clearly unsuitable if it passes too many of the lots of unsatisfactory quality or rejects too many of the lots of acceptable quality that are submitted to it.

This information is shown by the operating-characteristic (OC) curve of the plan. The ordinate of the OC curve shows the proportion L_p of lots that will be accepted when the fraction defective in submitted lots is p . The proportion of submitted lots of quality p that will be rejected is $1 - L_p$. The OC curve of Fig. 1.3 is typical: it shows a probability of 1 of accepting a lot having no defectives. As the fraction defective

TABLE 1.1
NORMAL DEVIATES EXCEEDED WITH GIVEN PROBABILITY

Values of K_ϵ for various ϵ , where $\frac{1}{\sqrt{2\pi}} \int_{K_\epsilon}^{\infty} e^{-\frac{x^2}{2}} dx = \epsilon$



ϵ	0.00	0.0	0.1	0.2	0.3	0.4
0	∞	∞	1.28155	0.84162	0.52440	0.25335
1	3.09023	2.32635	1.22653	0.80642	0.49585	0.22754
2	2.87816	2.05375	1.17499	0.77219	0.46770	0.20189
3	2.74778	1.88079	1.12639	0.73885	0.43991	0.17637
4	2.65207	1.75069	1.08032	0.70630	0.41246	0.15097
5	2.57583	1.64485	1.03643	0.67449	0.38532	0.12566
6	2.51214	1.55477	0.99446	0.64335	0.35846	0.10043
7	2.45726	1.47579	0.95417	0.61281	0.33185	0.07527
8	2.40892	1.40507	0.91537	0.58284	0.30548	0.05015
9	2.36562	1.34076	0.87790	0.55338	0.27932	0.02507

When $\epsilon > 0.5$, $K_\epsilon = -K_{1-\epsilon}$. When $\epsilon = 0.5$, $K_{0.5} = 0$.

The entries in column (ϵ) are additional digits for the values of ϵ shown in the top row. Thus, the entry 1.12639 in column (0.1) and row (3) corresponds with $\epsilon = 0.13$; similarly, the entry 2.74778 in column (0.00) and row (3) corresponds with $\epsilon = 0.003$.

A final 5 in *italic* indicates that, in rounding, the nearest *odd* digit should be used in the fourth decimal place. When a final 5 is *not* in *italic*, follow the usual rule of rounding 0.5 to the nearest even integer. Thus a final pair 55 becomes 6, 35 becomes 3, 85 becomes 9.

For a detailed table see *The Kelley Statistical Tables*; Table I gives values of K_ϵ (denoted by x) to 8 decimal places for values of ϵ (denoted by q) from 0 to 0.5 by steps of 0.0001. Alternatively, see Fisher and Yates, *Statistical Tables*; Table I gives values of K_ϵ (denoted by x) to 6 decimal places for values of ϵ (denoted by $P/2$) from 0 to 0.495 by steps of 0.005; also Table IX gives values of $K_\epsilon + 5$ to 4 decimal places for values of $1 - \epsilon$ from 0 to 0.980 by steps of 0.001 and from 0.9800 to 0.9999 by steps of 0.0001.

4.3. Illustration

To illustrate the use of equations (10), (11), and (12), suppose that lots are considered acceptable if the percent defective is 15 or less and unacceptable if the percent defective is 30 or more, and suppose the maximum producer's and consumer's risks are to be 1 percent and 2 percent, respectively. Then

$$p_1 = 0.15 \quad \alpha = 0.01 \quad (13)$$

$$p_2 = 0.30 \quad \beta = 0.02 \quad (14)$$

From Table 1.1, using only 4 decimal places, we find

$$K_1 = 1.0364 \quad K_\alpha = 2.3263 \quad (15)$$

$$K_2 = 0.5244 \quad K_\beta = 2.0537 \quad (16)$$

Substituting from (15) and (16) into (10) gives

$$\begin{aligned} k &= \frac{2.3263 \times 0.5244 + 2.0537 \times 1.0364}{2.3263 + 2.0537} \\ &= \frac{3.3484}{4.3800} \\ &= 0.7645 \end{aligned} \quad (17)$$

Substituting from (15) and (16) into (11) gives

$$\begin{aligned} N &= \frac{2 \times 4.3800^2 + 3.3484^2}{2 \times 0.5120^2} \\ &= 94.6 \end{aligned} \quad (18)$$

The same value of N results from substituting from (15), (16), and (17) into (12)

$$\begin{aligned} N &= \frac{0.7645^2 + 2 \left(\frac{4.3800}{0.5120} \right)^2}{2} \\ &= 1.2922 \times 73.1829 \\ &= 94.6. \end{aligned} \quad (19)$$

Thus, in this case a sample of 95 items would be drawn at random from the lot and a measurement of the characteristic being inspected would be made on each item of the sample. The sum of the measurements and the sum of their squares would be computed. These sums would be substituted into equations (4) and (6) to find the sample mean and standard deviation, \bar{x} and s . Finally, $\bar{x} + 0.7645s$ would be computed; if it exceeded U (the value of the quality characteristic above which an item is considered defective) the lot would be rejected, otherwise the lot would be accepted. (Actually, the abbreviated computational procedures described in Sec. 7 might be used.)

4.4. Adjustment of N

If the sample size given by (11) and (12) is too large, two new points may be selected in such a way that the OC curve will be less steep. For example, if p_1 and p_2 are kept at 15 and 30 percent but α and β are doubled, to 2 and 4 percent, N is reduced to 72; or if α and β are kept at 1 and 2 percent but p_1 and p_2 are changed to 10 and 35 percent, N becomes 32.

4.5. Adjustment of k with N Fixed

4.5.1. Formula.—If for some reason N is definitely fixed, the OC curve can be made to pass through any one point desired, say

$$p = p_1 \quad L_{p_1} = 1 - \alpha \quad (20)$$

by setting

$$k = \frac{K_1 \pm \sqrt{K_1^2 - ab}}{a} \quad (21)$$

where the plus sign is to be used if $\alpha > 0.5$ and the minus sign if $\alpha < 0.5$, and where

$$a = 1 - \frac{K_{\alpha}^2}{2(N-1)} \quad (22)$$

and

$$b = K_1^2 - \frac{K_{\alpha}^2}{N} \quad (23)$$

4.5.2. Example.—Suppose, for example, that a sample of 95 has been decided upon, and a sampling plan is desired such that the OC curve passes through the point defined by (14). Then (20) becomes

$$p_1 = 0.30 \quad L_{p_1} = 0.02 \quad (24)$$

and from Table 1.1 we find

$$K_1 = 0.5244 \quad K_{\alpha} = -2.0537 \quad (25)$$

Hence

$$\begin{aligned} a &= 1 - \frac{4.2177}{188} \\ &= 0.9776 \end{aligned} \quad (26)$$

$$\begin{aligned} b &= 0.2750 - \frac{4.2177}{95} \\ &= 0.2306 \end{aligned} \quad (27)$$

$$ab = 0.2254 \quad (28)$$

$$\begin{aligned} K_1^2 - ab &= 0.2750 - 0.2254 \\ &= 0.0496 \end{aligned} \quad (29)$$

$$\sqrt{K_1^2 - ab} = 0.2227 \quad (30)$$

$$\begin{aligned} k &= \frac{0.5244 + 0.2227}{0.9776} \\ &= 0.7642 \end{aligned} \quad (31)$$

This differs slightly from the value 0.7645 yielded by (17) for a sample of 95 and an OC curve passing through the points defined by (13) and (14). The value of k yielded by (31) would be equal (except for differences due to rounding) to that yielded by (17) if in (22) and (23) both N and $N-1$ were taken as 94.6.

4.5.3. A Special Case: Indifference Quality.—If N is fixed and k is to be selected so that the OC curve will pass through one specified point, this point might reasonably be chosen at the indifference quality p_0 . The indifference quality is the quality at which it is a matter of complete indifference whether the lot is accepted or rejected.* Lots of better

* For a discussion of the indifference quality as a key to the selection of sampling-inspection plans, see Statistical Research Group, *Sampling Inspection*, Chap. 15, Sec. 2.2.1.3, p. 145.

quality should be accepted more often than rejected, lots of worse quality should be rejected more often than accepted, and lots of the indifference quality should be accepted and rejected equally frequently. Thus, α in (20) becomes 0.5, K_α becomes 0, and (21) reduces to $k = K_0$, the normal deviate exceeded with probability equal to the indifference quality.

If k is determined from the indifference quality, it does not depend upon N , for the term in (22) and the term in (23) that involve N drop out when $K_\alpha = 0$. Thus if k is determined from the indifference quality, changes in N will not change the value of p for which acceptance and rejection are equally likely, nor will they require changes in k . Roughly speaking, changes in N affect the steepness of the curve, while changes in k affect its location with respect to the quality scale.

4.6. Approximations in the Plan

Three kinds of approximation are involved in using formulas (10), (11), and (12). First, there is the approximation involved in assuming the quality characteristic to be normally distributed. Second, certain mathematical approximations are involved in the derivation of the formulas (see Sec. 11.2). Third, the value of N given by formulas (11) and (12) is not ordinarily an integer, so an approximation is involved in substituting an integer. The effect of the first approximation is discussed later (Sec. 9.4). Even if the quality characteristic were exactly normally distributed, the result of the second and third approximations would be that the true OC curve would not pass precisely through the points intended; but it would come sufficiently close for all practical purposes. In the present illustration, for example, taking $N = 95$ and $k = 0.7645$ results in a producer's risk of 1 percent at a percent defective of 15.04 instead of 15. The inaccuracies due to the second and third approximations tend to be larger for smaller samples, both because the effect of the mathematical approximations is larger and because the effect of rounding N is, on the average, larger; this point is discussed further in Secs. 4.7 and 11.2.

4.7. Table of N and k

Table 1.2 contains values of N and k for 151 combinations of p_1 and p_2 . The values of p_1 in the table range from 0.001 to 0.05; the values of p_2 vary from about $\frac{1}{3}p_1$ or $\frac{3}{2}p_1$ up to $10p_1$ or more. The values of α are in all cases 0.05 and the values of β are 0.10. The values of N and k have been computed by methods explained in Sec. 11.5 that do not involve the mathematical approximations used in formulas (10) and (11) or (12), so they may be slightly different from, and more accurate than, the values given by (10) and (11) or (12). This is especially true when N is small, not only because of the mathematical approximations under-

TABLE 1.2.—(Continued)

Intended p_1	Intended p_2	N	k	True p_1	True p_2
0.005	0.0075	1713	2.4952	0.0050	0.0075
	0.01	547	2.4357	0.0050	0.0100
	0.012	328	2.3967	0.0050	0.0120
	0.015	197	2.3482	0.0050	0.0151
	0.02	114	2.2824	0.0050	0.0202
	0.025	80	2.2297	0.0051	0.0253
	0.03	61	2.1886	0.0050	0.0302
	0.035	50	2.1546	0.0050	0.0349
	0.04	42	2.1272	0.0049	0.0395
	0.05	32	2.0723	0.0049	0.0492
	0.06	26	2.0265	0.0049	0.0587
	0.07	22	1.9874	0.0049	0.0680
0.0075	0.01	2907	2.3728	0.0075	0.0100
	0.012	1039	2.3339	0.0075	0.0120
	0.015	451	2.2851	0.0075	0.0150
	0.02	208	2.2198	0.0075	0.0201
	0.025	130	2.1700	0.0075	0.0250
	0.03	93	2.1274	0.0075	0.0299
	0.035	72	2.0891	0.0075	0.0350
	0.04	58	2.0555	0.0075	0.0401
	0.05	42	1.9996	0.0075	0.0500
	0.06	33	1.9501	0.0075	0.0601
	0.07	27	1.9093	0.0075	0.0700
	0.08	23	1.8714	0.0075	0.0800
0.01	0.015	1231	2.2385	0.0100	0.0150
	0.02	389	2.1733	0.0100	0.0200
	0.025	208	2.1205	0.0100	0.0251
	0.03	137	2.0761	0.0101	0.0302
	0.035	101	2.0372	0.0101	0.0353
	0.04	79	2.0041	0.0101	0.0403
	0.045	64	1.9776	0.0100	0.0451
	0.05	54	1.9527	0.0099	0.0499
	0.06	41	1.9007	0.0100	0.0602
	0.07	33	1.8561	0.0101	0.0704
	0.08	28	1.8271	0.0099	0.0787
	0.09	24	1.7974	0.0098	0.0880
	0.10	21	1.7643	0.0099	0.0979

TABLE 1.2

VALUES OF N AND k FOR VARIOUS COMBINATIONS OF p_1 AND p_2 WHEN $\alpha = 0.05$ AND $\beta = 0.10$

N is the sample size; k is the multiple of the standard deviation in the criterion $\bar{x} + ks \leq U$ for accepting the lot, where U is the value above which the characteristic being inspected is regarded as defective; p_1 is the acceptable quality level (AQL); p_2 is the lot tolerance percent defective (LTPD); $\alpha = 0.05$ is the producer's risk; and $\beta = 0.10$ is the consumer's risk. The true p_1 and true p_2 are the values at which, for the corresponding N and k , $\alpha = 0.05$ and $\beta = 0.10$; the difference between the true and intended values of p_1 and p_2 arises from the fact that N must be an integer.

This table has been computed with the aid of Table IV in Johnson and Welch, "Applications of the Non-central t -Distribution." The entries for N , k , true p_1 , and true p_2 are therefore slightly more accurate than those given by formulas (10), (11) or (12), and (42), respectively. See Sec. 11.5 on the construction of this table.

Intended p_1	Intended p_2	N	k	True p_1	True p_2
0.001	0.0015	3177	3.0214	0.0010	0.0015
	0.002	1032	2.9711	0.0010	0.0020
	0.0025	567	2.9311	0.0010	0.0025
	0.003	381	2.8979	0.0010	0.0030
	0.004	226	2.8441	0.0010	0.0040
	0.005	161	2.8018	0.0010	0.0050
	0.006	125	2.7600	0.0010	0.0061
	0.007	103	2.7359	0.0010	0.0071
	0.008	87	2.7153	0.0010	0.0080
	0.009	76	2.6832	0.0010	0.0092
	0.01	68	2.6725	0.0010	0.0099
	0.012	56	2.6220	0.0010	0.0122
	0.015	45	2.5730	0.0010	0.0153
	0.02	34	2.5208	0.0010	0.0201
	0.025	28	2.4712	0.0010	0.0250
	0.03	24	2.4392	0.0010	0.0294
	0.035	21	2.3930	0.0010	0.0351
	0.04	19	2.3745	0.0010	0.0389
	0.05	16	2.3059	0.0010	0.0494
	0.06	14	2.2570	0.0010	0.0590
0.0025	0.004	1677	2.7199	0.0025	0.0040
	0.005	736	2.6772	0.0025	0.0050
	0.006	443	2.6413	0.0025	0.0060
	0.0075	268	2.5967	0.0025	0.0075
	0.01	158	2.5376	0.0025	0.0101
	0.012	118	2.4979	0.0025	0.0121
	0.015	86	2.4576	0.0025	0.0149
	0.02	59	2.3875	0.0025	0.0202
	0.025	46	2.3410	0.0025	0.0249
	0.03	37	2.2981	0.0025	0.0301
	0.035	32	2.2610	0.0025	0.0348
	0.04	28	2.2354	0.0025	0.0391
	0.05	22	2.1721	0.0025	0.0501
	0.06	19	2.1321	0.0025	0.0585

0.4029. Thus, even for this case where N is only 6, it is questionable whether the greater accuracy of Table 1.2 or of the adjusted k , as compared with formulas (10) and (11) or (12), is of substantial value for most practical purposes; and for larger values of N the differences are even less important.

5. AMOUNT OF INSPECTION

5.1. Comparison with Attribute Inspection

If each item were classified simply defective or nondefective and the acceptability of the lot judged by the number of defectives in a single sample, a sample of 145 would be required for an OC curve passing through the points defined by (13) and (14).^{*} If the sampling were done sequentially by attributes, the average number of items inspected would be 20 for lots with no defectives, 63 for lots 15 percent defective, 133 for lots 22 percent defective, 61 for lots 30 percent defective, and 7 for lots 100 percent defective.[†]

TABLE 1.3
SAMPLE SIZES FOR EIGHT PAIRS OF SINGLE-SAMPLING PLANS BASED ON ATTRIBUTES
AND VARIABLES
 $\alpha = 0.05$, $\beta = 0.10$ for all plans
 N_a = sample size for attributes
 N_t = sample size for variables

Plan number	p_1	p_2	N_t	N_a	N_a/N_t	Saving ($N_a - N_t$)/ N_a percent
1	0.001	0.002	1,032	12,476	12.09	91.7
2	0.001	0.06	14	46	3.29	69.6
3	0.01	0.015	1,231	4,185	3.40	70.6
4	0.01	0.10	21	44	2.10	52.3
5	0.05	0.07	661	1,199	1.81	44.9
6	0.05	0.40	6	10	1.67	40.0
7	0.15	0.20	323	493	1.53	34.5
8	0.15	0.40	17	26	1.53	34.6

For attributes the sample sizes have been computed as explained in Chap. 7. For variables they have been computed by the method described in Sec. 11.5 of this chapter, which sometimes gives values slightly different from, and slightly more accurate than, those given by formulas (11) and (12).

^{*} See Chap. 7, Sec. 3, equation (21) and first footnote on p. 260.

[†] See Statistical Research Group, *Sequential Analysis*, Sec. 2 (second revision), where the example defined by equations (13) and (14) above is treated in some detail. Sequential analysis also can be used with variables (see Sec. 11.5 below) and will result in a reduction in the average amount of inspection similar to that with attributes—roughly 40 to 60 percent (see *Sequential Analysis*, Appendix A, p. A.03).

The savings in the number of items inspected by using variables instead of attributes depends partly upon the steepness of the OC curve and partly upon its location. The steeper the OC curve, the greater the saving from using variables. The better the lot qualities involved (that is, the smaller the percentages defective), the greater the saving. Eight comparisons of attribute and variables plans are shown in Table 1.3. In each case, $\alpha = 0.05$ and $\beta = 0.10$. N_a and N_t represent the sample sizes for single-sampling plans based on attributes and variables, respectively.

5.2. Comparison with Variables Inspection When the Standard Deviation Is Known

If the true standard deviation of the characteristic being inspected is given, the proportion defective depends only upon the mean, being p_1 or less if the mean is $U - K_1\sigma$ or less, and p_2 or more if the mean is $U - K_2\sigma$ or more.* If the standard deviation were known, a sample of 73 would be required for an OC curve passing through the points defined by (13) and (14). The reduction of 22 observations (23 percent) from the 95 needed when the standard deviation is not known thus represents

TABLE 1.4

SAMPLE SIZES FOR EIGHT PAIRS OF SINGLE-SAMPLING VARIABLES PLANS BASED ON
 • KNOWN AND UNKNOWN STANDARD DEVIATIONS
 $\alpha = 0.05$, $\beta = 0.10$ for all plans
 N_t = sample size with standard deviation unknown
 N_m = sample size with standard deviation known

Plan number	p_1	p_2	N_t	N_m	N_t/N_m	Saving ($N_t - N_m$)/ N_t percent
1	0.001	0.002	1,032	190	5.43	81.6
2	0.001	0.06	14	4	3.50	71.4
3	0.01	0.015	1,231	351	3.51	71.5
4	0.01	0.10	21	8	2.62	61.9
5	0.05	0.07	661	300	2.20	54.6
6	0.05	0.40	6	4	1.50	33.3
7	0.15	0.20	323	226	1.43	30.0
8	0.15	0.40	17	14	1.21	17.6

For the known standard deviation, the sample sizes are given by $1/a$, where a is defined by equation (137), Sec. 11.1 of this chapter. For the unknown standard deviation they have been computed by the method described in Sec. 11.3 of this chapter, which sometimes gives values slightly different from, and slightly more accurate than, those given by formulas (11) and (12).

the savings in inspection yielded by knowledge of the standard deviation.† This saving, like that yielded by sufficient knowledge of the form of

* The use of variables in inspection for proportion defective when the standard deviation is known is discussed by Romig, *Allowable Average in Sampling Inspection*.

† Incidentally, 22 is the number of observations required for an OC curve satisfying (13) and (14) if the true mean is known and only the standard deviation need be

0.4029. Thus, even for this case where N is only 6, it is questionable whether the greater accuracy of Table 1.2 or of the adjusted k , as compared with formulas (10) and (11) or (12), is of substantial value for most practical purposes; and for larger values of N the differences are even less important.

5. AMOUNT OF INSPECTION

5.1. Comparison with Attribute Inspection

If each item were classified simply defective or nondefective and the acceptability of the lot judged by the number of defectives in a single sample, a sample of 145 would be required for an OC curve passing through the points defined by (13) and (14).^{*} If the sampling were done sequentially by attributes, the average number of items inspected would be 20 for lots with no defectives, 63 for lots 15 percent defective, 133 for lots 22 percent defective, 61 for lots 30 percent defective, and 7 for lots 100 percent defective.[†]

TABLE 1.3
SAMPLE SIZES FOR EIGHT PAIRS OF SINGLE-SAMPLING PLANS BASED ON ATTRIBUTES
AND VARIABLES
 $\alpha = 0.05$, $\beta = 0.10$ for all plans
 N_a = sample size for attributes
 N_t = sample size for variables

Plan number	p_1	p_2	N_t	N_a	N_a/N_t	Saving ($N_a - N_t$)/ N_a percent
1	0.001	0.002	1,032	12,476	12.09	91.7
2	0.001	0.06	14	46	3.29	69.6
3	0.01	0.015	1,231	4,185	3.40	70.6
4	0.01	0.10	21	44	2.10	52.3
5	0.05	0.07	661	1,199	1.81	44.9
6	0.05	0.40	6	10	1.67	40.0
7	0.15	0.20	323	493	1.53	34.5
8	0.15	0.40	17	26	1.53	34.6

For attributes the sample sizes have been computed as explained in Chap. 7. For variables they have been computed by the method described in Sec. 11.5 of this chapter, which sometimes gives values slightly different from, and slightly more accurate than, those given by formulas (11) and (12).

* See Chap. 7, Sec. 3, equation (21) and first footnote on p. 260.

† See Statistical Research Group, *Sequential Analysis*, Sec. 2 (second revision), where the example defined by equations (13) and (14) above is treated in some detail. Sequential analysis also can be used with variables (see Sec. 11.6 below) and will result in a reduction in the average amount of inspection similar to that with attributes—roughly 40 to 60 percent (see *Sequential Analysis*, Appendix A, p. A.03).

The savings in the number of items inspected by using variables instead of attributes depends partly upon the steepness of the OC curve and partly upon its location. The steeper the OC curve, the greater the saving from using variables. The better the lot qualities involved (that is, the smaller the percentages defective), the greater the saving. Eight comparisons of attribute and variables plans are shown in Table 1.3. In each case, $\alpha = 0.05$ and $\beta = 0.10$. N_a and N_t represent the sample sizes for single-sampling plans based on attributes and variables, respectively.

5.2. Comparison with Variables Inspection When the Standard Deviation Is Known

If the true standard deviation of the characteristic being inspected is given, the proportion defective depends only upon the mean, being p_1 or less if the mean is $U - K_1\sigma$ or less, and p_2 or more if the mean is $U - K_2\sigma$ or more.* If the standard deviation were known, a sample of 73 would be required for an OC curve passing through the points defined by (13) and (14). The reduction of 22 observations (23 percent) from the 95 needed when the standard deviation is not known thus represents

TABLE 1.4

SAMPLE SIZES FOR EIGHT PAIRS OF SINGLE-SAMPLING VARIABLES PLANS BASED ON
 KNOWN AND UNKNOWN STANDARD DEVIATIONS
 $\alpha = 0.05$, $\beta = 0.10$ for all plans
 N_t = sample size with standard deviation unknown
 N_m = sample size with standard deviation known

Plan number	p_1	p_2	N_t	N_m	N_t/N_m	Saving ($N_t - N_m$)/ N_t percent
1	0.001	0.002	1,032	190	5.43	81.6
2	0.001	0.06	14	4	3.50	71.4
3	0.01	0.015	1,231	351	3.51	71.5
4	0.01	0.10	21	8	2.62	61.9
5	0.05	0.07	661	300	2.20	54.6
6	0.05	0.40	6	4	1.50	33.3
7	0.15	0.20	323	226	1.43	30.0
8	0.15	0.40	17	14	1.21	17.6

For the known standard deviation, the sample sizes are given by $1/a$, where a is defined by equation (137), Sec. 11.1 of this chapter. For the unknown standard deviation they have been computed by the method described in Sec. 11.5 of this chapter, which sometimes gives values slightly different from, and slightly more accurate than, those given by formulas (11) and (12).

the savings in inspection yielded by knowledge of the standard deviation.† This saving, like that yielded by sufficient knowledge of the form of

* The use of variables in inspection for proportion defective when the standard deviation is known is discussed by Romig, *Allowable Average in Sampling Inspection*.

† Incidentally, 22 is the number of observations required for an OC curve satisfying (13) and (14) if the true mean is known and only the standard deviation need be

distribution to permit the use of variables instead of attributes, varies with the OC curve. Comparisons between N_i , the sample size for the variables plans with unknown mean and standard deviation, and N_m , the sample size with known standard deviation, are shown in Table 1.4 for eight plans defined by the same pairs of OC points used in Table 1.3. In general, the percentage saving, computed before N_i and N_m are rounded to integers, is $100k^2/(k^2 + 2)$, but for small samples it may differ from this on account of rounding.

8. OPERATING-CHARACTERISTIC CURVE

6.1. Introduction

The values of k and N may be obtained from (10) and (11) or (12) so that the OC curve will pass through two specified points. They may be obtained by selecting N arbitrarily and computing k from (21) so that the OC curve will pass through one specified point. They may both be determined arbitrarily. Regardless of how they are chosen, their effects must be evaluated in terms of the OC curve to which they give rise. How will they operate with lots of every quality that might conceivably be offered? If a lot is good, what is the risk that the sample from it will fail to meet the acceptance requirement? If a lot is bad, what is the risk that the sample will satisfy the acceptance criterion? The OC curve shows, for every possible lot quality p , the probability L_p that a lot of that quality will, if submitted, be accepted on the basis of the sampling plan.

6.2. Five-point OC Curve

Three points on the OC curve are easily obtained: (1) When there are no defectives in the lot, acceptance is certain; (2) when the lot contains only defectives, rejection is certain; (3) when the proportion of defectives in the lot is p_0 , such that $K_{p_0} = k$, acceptance and rejection are equally likely. Thus three points on the OC curve are given by

$$p = 0 \quad L_0 = 1 \quad (32)$$

$$p = p_0 \quad L_{p_0} = 0.5 \quad (33)$$

$$p = 1 \quad L_1 = 0 \quad (34)$$

used in testing percent defective. In general, if N_i is the number of observations required when neither the mean nor the standard deviation is known, N_m the number required when the standard deviation is known, and N_s the number required when the mean is known, the relation $N_i = N_m + N_s$ will hold; in fact, $N_m = 2N_i/(k^2 + 2)$ and $N_s = k^2N_i/(k^2 + 2)$. See Chap. 8 for methods of determining the sample size N_s when inspection is based on the standard deviation; the sample size N_m , when inspection is based on the mean, can be determined from equation (148) in Sec. 11.1 of this chapter; it is $1/a$, where a is defined by equation (137).

where p_0 is the probability that a normal deviate will exceed k . If k and N have been determined by (10) and (11) or (12), the OC curve will also pass through the two points

$$p = p_1 \quad L_{p_1} = 1 - \alpha \quad (35)$$

$$p = p_2 \quad L_{p_2} = \beta \quad (36)$$

A sketch of the OC curve made from these five points is sufficient for many purposes. For the illustrative example of Sec. 4.3, for example, we have

$$p = 0 \quad L_0 = 1 \quad (37)$$

$$p_1 = 0.15 \quad L_{0.15} = 0.99 \quad (38)$$

$$p_0 = 0.2223 \quad L_{0.2223} = 0.5 \quad (39)$$

$$p_2 = 0.30 \quad L_{0.30} = 0.02 \quad (40)$$

$$p = 1 \quad L_1 = 0 \quad (41)$$

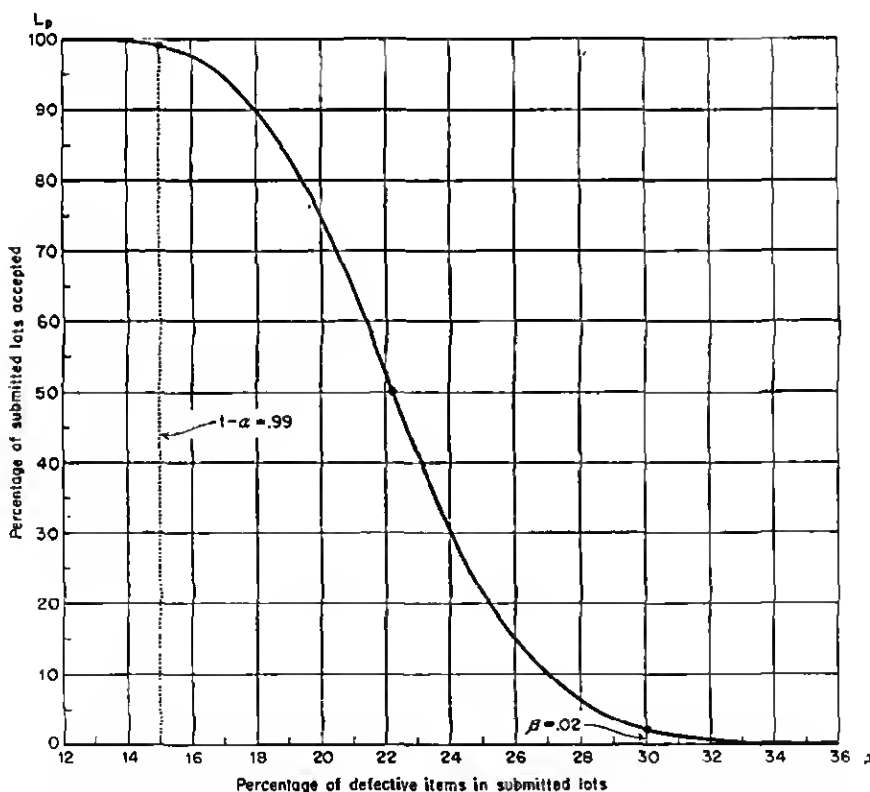


FIG. 1.4.—Operating-characteristic (OC) curve for a variables inspection plan for percent defective; $N = 95$, $k = 0.7645$. [Data from Table 1.6, columns (6), (7), (8).]

The central three of these five points are represented by dots in Fig. 1.4; the two extreme points are not shown because of the incompleteness of the p scale.

6.3. Detailed OC Curve

As many points on the OC curve as desired may be found from the following formula, which expresses the normal deviate corresponding with the lot quality in terms of the normal deviate corresponding with any given probability of acceptance:

$$K_p = k - K_{L_p} \sqrt{\frac{1}{N} + \frac{k^2}{2(N-1)}} \quad (42)$$

Formula (42) yields the normal deviate corresponding with p . The value of p can be found from Table 1.5, which shows the probabilities of exceeding various normal deviates.

If p is to be computed for a number of values of L_p in order to plot the entire OC curve, it is convenient while computing (42) to compute

$$K_{p'} = k + K_{L_p} \sqrt{\frac{1}{N} + \frac{k^2}{2(N-1)}} \quad (43)$$

If it is desired to find the probability of acceptance for a lot of given quality, (42) and (43) can be rewritten as

$$K_{L_p} = \frac{k - K_p}{\sqrt{\frac{1}{N} + \frac{k^2}{2(N-1)}}} \quad (44)$$

$$K_{L_{p'}} = -K_{L_p} \quad (45)$$

6.3.1. Illustrative Computation for One Point.—To illustrate the use of formulas (42) and (43), consider an acceptance-inspection plan defined by $N = 95$ and $k = 0.7645$. For what lot quality is the probability of rejection 1 percent?

We have

$$N = 95 \quad k = 0.7645 \quad K_{0.99} = -2.32635 \quad (46)$$

Then

$$\sqrt{\frac{1}{N} + \frac{k^2}{2(N-1)}} = 0.11677 \quad (47)$$

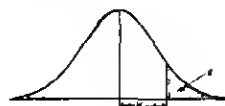
$$K_{L_p} \sqrt{\frac{1}{N} + \frac{k^2}{2(N-1)}} = -0.27165 \quad (48)$$

Substituting into (42),

$$K_p = 1.03615 \quad (49)$$

TABLE 1.5
PROBABILITIES CORRESPONDING WITH GIVEN NORMAL DEVIATES

Values of ϵ for various K_ϵ , where $\frac{1}{\sqrt{2\pi}} \int_{K_\epsilon}^{\infty} e^{-\frac{x^2}{2}} dx = \epsilon$



K_ϵ	0	1	2	3	4	5	6	7	8	9
0.0	0.5000	0.4960	0.4920	0.4880	0.4840	0.4801	0.4761	0.4721	0.4681	0.4641
0.1	0.4602	0.4562	0.4522	0.4483	0.4443	0.4404	0.4364	0.4325	0.4286	0.4247
0.2	0.4207	0.4168	0.4129	0.4090	0.4052	0.4013	0.3974	0.3936	0.3897	0.3859
0.3	0.3821	0.3783	0.3745	0.3707	0.3669	0.3632	0.3594	0.3557	0.3520	0.3483
0.4	0.3446	0.3409	0.3372	0.3336	0.3300	0.3264	0.3228	0.3192	0.3156	0.3121
0.5	0.3085	0.3050	0.3015	0.2981	0.2946	0.2912	0.2877	0.2843	0.2810	0.2776
0.6	0.2743	0.2709	0.2676	0.2643	0.2611	0.2578	0.2546	0.2514	0.2483	0.2451
0.7	0.2420	0.2389	0.2358	0.2327	0.2296	0.2266	0.2236	0.2206	0.2177	0.2148
0.8	0.2119	0.2090	0.2061	0.2033	0.2005	0.1977	0.1949	0.1922	0.1894	0.1867
0.9	0.1841	0.1814	0.1788	0.1762	0.1736	0.1711	0.1685	0.1660	0.1635	0.1611
1.0	0.1587	0.1562	0.1539	0.1515	0.1492	0.1469	0.1446	0.1423	0.1401	0.1379
1.1	0.1357	0.1335	0.1314	0.1292	0.1271	0.1251	0.1230	0.1210	0.1190	0.1170
1.2	0.1151	0.1131	0.1112	0.1093	0.1075	0.1056	0.1038	0.1020	0.1003	0.0985
1.3	0.0968	0.0951	0.0934	0.0918	0.0901	0.0885	0.0869	0.0853	0.0838	0.0823
1.4	0.0808	0.0793	0.0778	0.0764	0.0749	0.0735	0.0721	0.0708	0.0694	0.0681
1.5	0.0668	0.0655	0.0643	0.0630	0.0618	0.0606	0.0594	0.0582	0.0571	0.0559
1.6	0.0548	0.0537	0.0526	0.0516	0.0505	0.0495	0.0485	0.0475	0.0465	0.0455
1.7	0.0446	0.0436	0.0427	0.0418	0.0409	0.0401	0.0392	0.0384	0.0375	0.0367
1.8	0.0359	0.0351	0.0344	0.0336	0.0329	0.0322	0.0314	0.0307	0.0301	0.0294
1.9	0.0287	0.0281	0.0274	0.0268	0.0262	0.0256	0.0250	0.0244	0.0239	0.0233
2.0	0.0228	0.0222	0.0217	0.0212	0.0207	0.0202	0.0197	0.0192	0.0188	0.0183
2.1	0.0179	0.0174	0.0170	0.0166	0.0162	0.0158	0.0154	0.0150	0.0146	0.0143
2.2	0.0139	0.0136	0.0132	0.0129	0.0125	0.0122	0.0119	0.0116	0.0113	0.0110
2.3	0.0107	0.0104	0.0102	0.0099	0.0096	0.0094	0.0091	0.0089	0.0087	0.0084
2.4	0.0082	0.0080	0.0078	0.0075	0.0073	0.0071	0.0069	0.0068	0.0066	0.0064
2.5	0.0062	0.0060	0.0059	0.0057	0.0055	0.0054	0.0052	0.0051	0.0049	0.0048
2.6	0.0047	0.0045	0.0044	0.0043	0.0041	0.0040	0.0039	0.0038	0.0037	0.0036
2.7	0.0035	0.0034	0.0033	0.0032	0.0031	0.0030	0.0029	0.0028	0.0027	0.0026
2.8	0.0026	0.0025	0.0024	0.0023	0.0023	0.0022	0.0021	0.0021	0.0020	0.0019
2.9	0.0019	0.0018	0.0018	0.0017	0.0016	0.0016	0.0015	0.0015	0.0014	0.0014
3.0	0.0013	0.0013	0.0013	0.0012	0.0012	0.0011	0.0011	0.0011	0.0010	0.0010

The entries in row (K_ϵ) are additional digits for the values of K_ϵ shown in the first column. Thus, the entry 0.0934 in column (2) and row (1.3) corresponds with $K_\epsilon = 1.32$; similarly, the entry 0.4840 in column (4) and row (0.0) corresponds with $K_\epsilon = 0.04$.

A 5 in *italic* indicates that, in rounding, the nearest *odd* digit should be used in the preceding decimal place. When a 5 is not in *italic*, follow the usual rule of rounding to the nearest even digit. Thus a final pair 55 becomes 6, 35 becomes 3, 85 becomes 9.

For a detailed table see New York Mathematical Tables Project *Tables of Probability Functions*. Table I gives values of $1 - 2\epsilon$ to 15 decimal places for values of K_ϵ (denoted by x) from 0 to 1 by steps of 0.0001, and for all values of K_ϵ above 1 by steps of 0.001.

Interpolating linearly in Table 1.5, we find $p = 15.01$ percent.* Similarly, on substituting into (43) we find $K_p = 0.49285$; so $p = 31.11$ percent for $L_p = 0.01$.

6.3.2. Work Sheet for Detailed OC Curve.—When a number of points on the OC curve are needed, it is convenient to arrange the computations in a systematic way, as for example that shown in Table 1.6, which contains the computations for the OC curve of the example of Sec. 4.3.

TABLE 1.6
WORK SHEET FOR OPERATING-CHARACTERISTIC CURVE

Basic quantities: $N = 95$; $k = 0.7645$; $S = \sqrt{\frac{1}{N} + \frac{k^2}{2(N-1)}} = 0.11677$

(1) L_p	(2) K_{L_p}	(3) $S \times (2)$	(4) $k - (3)$	(5) $k + (3)$	(6) p	(7) p'	(8) $1 - (1) = L_{p'}$
0.005	2.57583	0.30078	0.46372	1.06528	0.321	0.143	0.995
0.01	2.32635	0.27165	0.49285	1.03615	0.311	0.150	0.99
0.02	2.05375	0.23982	0.52468	1.00432	0.300	0.158	0.98
0.03	1.88079	0.21962	0.54488	0.98412	0.293	0.163	0.97
0.04	1.75069	0.20443	0.56007	0.96893	0.288	0.166	0.96
0.05	1.64485	0.19207	0.57243	0.95657	0.284	0.169	0.95
0.15	1.03643	0.12102	0.64348	0.88552	0.260	0.188	0.85
0.25	0.67449	0.07876	0.68574	0.84326	0.246	0.200	0.75
0.50	0	0	0.76450	0.76450	0.222	0.222	0.50

First, enter at the top of the sheet the three basic quantities N , k , and S , S being defined by the left-hand side of equation (47).

Second, enter in column (1) various ordinates L_p less than or equal to 0.5 for which the corresponding abscissas p are to be computed.

Third, enter in column (2) values K_{L_p} of the normal deviates corresponding with the values of L_p ; these may be obtained from Table 1.1.

Fourth, enter in column (3) the products of S by the normal deviates in column (2).

Fifth, subtract from k the entries in column (3) and enter the differences in column (4).

Sixth, add to k the entries in column (3) and enter the sums in column (5).

Seventh, enter in column (6) the probabilities corresponding with the normal deviates in column (4); these may be obtained from Table 1.5.

Eighth, enter in column (7) the probabilities corresponding with the normal deviates in column (5); these may be obtained from Table 1.5.

* The value 15.04 percent stated in Sec. 4.6 was obtained by an exact method, described in Sec. 11.5, which does not involve the mathematical approximations involved in formulas (42) and (43).

Ninth, subtract from 1 the values of L_p shown in the first column and enter the differences in column (8).

Tenth, plot one-half the OC curve, using as abscissas the values of p shown in column (6) and as ordinates the corresponding values of L_p shown in column (1).

Eleventh, plot the other half of the OC curve, using as abscissas the values of p' shown in column (7) and as ordinates the corresponding values of L_p shown in column (8).

The OC curve corresponding with Table 1.6 is shown in Fig. 1.4. The three dots represent the central three points of Sec. 6.2, formulas (38) to (40).

7. TECHNIQUES OF APPLYING THE PLAN

7.1. Introduction

Without calculating either the mean \bar{x} or the standard deviation s , the computing can be arranged to show whether the acceptance criterion

$$\bar{x} + ks \leq U \quad (50)$$

has been met. This is done partly by rearranging formula (50), and partly by carrying out in advance certain steps in the computations that do not depend upon the data.

There is some question as to how much the computational simplifications add to the procedure. They are likely to be welcomed by those who consider the standard deviation "too complicated for practical purposes," and who would therefore reject (50) as an acceptance criterion if it were not emphasized that the standard deviation need not actually be computed. Those holding this view, however, often have had little or no practical experience in computing or using standard deviations, and what experience they have had may have been with inefficient computing techniques. In fact, statisticians do not generally realize how often standard deviations are computed by the naïve use of formula (5). The mean is calculated, then the N differences between it and the observations are found and recorded; these are then squared and added, the sum divided by $N - 1$, and the square root taken. Not only is this process tedious and liable to error, but there is an inherent loss of accuracy from rounding the differences. The standard deviation should, of course, be computed from formula (6). With modern computing machines it can be calculated simultaneously with the calculation of the mean and with very little extra trouble. With the Monroe Model AA-1, for example, the first observation is set in the keyboard and the \times and $=$ keys pressed in rapid succession; then the next observation is set on the keyboard and the same two keys pressed again; and so on. When this has been completed for all N observations, which takes little more time and trouble than adding the

data, the quantities Σx and Σx^2 needed for formula (6) are found in the upper and lower dials, respectively.*

Another reason computational simplifications are perhaps less important than they may at first appear is that the actual values of the mean and standard deviation, although not needed for acceptance purposes, are valuable for other purposes, as, for example, process control. In fact, the conditions under which inspection is based on variables instead of attributes are likely to be those where the cost of obtaining each observation is so high, because of destruction of test items, use of costly test equipment, and so forth, that the cost of analyzing the data is almost negligible in comparison.

7.2. Computational Procedure†

7.2.1. Formulas.—For any given plan of action, determined by a fixed N and k , the left-hand side of formula (50) depends only upon the sum of the observations Σx and the sum of the squares of the observations Σx^2 . Let

$$X = \Sigma x \quad (51)$$

$$Y = \Sigma x^2 \quad (52)$$

These two sums may be computed easily and simultaneously on any automatic computing machine. If only an adding machine is available, Y can be obtained with the aid of a table of squares, for example, Barlow's.

If k is positive, it may be noted first that if

$$X > NU \quad (53)$$

the lot may be rejected without regard to Y . In that case \bar{x} exceeds U ; since s must be positive, $\bar{x} + ks$ will still further exceed U .

Second, it may be noted that if

$$Y \leq \frac{U^2(N-1)}{k^2+1} \quad (54)$$

the lot may be accepted without regard to X . Equation (72) below is, however, more efficient than (54) in permitting immediate acceptance.

* This paragraph indicates only the general nature of the procedures for computing the standard deviation. Further simplifications are usually possible. Also, the use of the Monroe Model AA-1 as an illustration does not imply that this make or model is superior to other automatic calculating machines. Both the Fridén and Marchant companies make excellent machines. The Statistical Research Group attempted to evaluate various makes and models on the basis of about 660 machine-months of experience in its offices from 1942 to 1945. The evidence failed to show any one make or model to be best, although there were interesting differences. The terms "upper dials" and "lower dials" used in this chapter apply to Marchant and Monroe calculators but should be interchanged for Fridén calculators.

† For a discussion of the accuracy with which the measurements should be made, see Chap. 4.

Third, if neither inequality (53) nor (54) is satisfied, the lot is accepted if

$$Y \leq aX^2 - bX + c \quad (55)$$

where

$$a = \frac{Nk^2 + N - 1}{N^2k^2} \quad (56)$$

$$b = \frac{2U(N - 1)}{Nk^2} \quad (57)$$

$$c = \frac{U^2(N - 1)}{k^2} \quad (58)$$

If inequality (55) is not fulfilled, the lot is rejected. The values of a , b , and c given by (56), (57), and (58) do not depend upon the outcome of the inspection but only upon the sampling plan defined by N and k and upon the definition of a defective item as given by U . When a sample has been inspected, the values of X and Y are obtained from the observations and substituted into (55). Formula (78) below provides an additional condition, linear in X , that may be inserted between (54) and (55), which are, respectively, independent of and quadratic in X ; formula (78), however, requires a preliminary estimate of the region in which the sample mean is likely to lie.

7.2.2. Example.—Consider a sampling plan in which $N = 95$ and $k = 0.7645$. Suppose that for the characteristic being inspected values in excess of $U = 35$ are regarded as defective.

From these values of N , k , and U we have, from (56), (57), and (58),

$$a = 0.0283471 \quad (59)$$

$$b = 118.508 \quad (60)$$

$$c = 197,019 \quad (61)$$

Now suppose that a sample shows

$$X = \Sigma x = 2,872 \quad (62)$$

$$Y = \Sigma x^2 = 89,175 \quad (63)$$

First, it is noted that, since

$$X < 3,325 \quad (64)$$

inequality (53) is not fulfilled, so immediate rejection is not called for. Second, it is noted that, since

$$Y > 72,675, \quad (65)$$

immediate acceptance is not possible on the basis of (54). Applying (55), it is found that

$$Y < 90,482 \quad (66)$$

Therefore, the lot is acceptable.

In this example

$$\bar{x} = 30.232 \quad (67)$$

$$s = 5.000 \quad (68)$$

$$\bar{x} + ks = 34.05 \quad (69)$$

and, since this is less than 35, acceptance is indicated.

7.3. Graphical Procedure

7.3.1. Original Data.—The computing involved in substituting X and X^2 into formula (55) may be avoided by the use of a chart. Values of X may be plotted horizontally and values of Y vertically, and a curve (parabola) drawn showing for each value of X the minimum value of Y , Y_* , requiring rejection as determined from formula (55) using the equality sign. Then as soon as X and Y are determined from a sample, a point may be plotted on the chart. If the point falls on or below the parabola, the lot is accepted; if the point falls above the parabola, the lot is rejected.

Figure 1.5 shows such a curve for the example of Sec. 7.2.2, and the point corresponding with the sample of that example is shown.* Also shown in the figure is a lower boundary for the acceptance region. This lower boundary arises from the fact that, for any given sum of the observations X , it is algebraically impossible for the sum of the squares of the observations Y to be less than a certain minimum; this minimum is the value Y takes when all the observations are equal, namely,

$$Y_* = \frac{X^2}{N} \quad (70)$$

If a sample point should fall on the lower line, it would indicate that the standard deviation was zero. A sample point cannot fall below the lower line unless there is an error in the calculations.

For practical purposes only a part of the range of X shown in Fig. 1.5 would be needed, for example, that enclosed in the rectangle. Confining the chart to this region, as in Fig. 1.6, permits the use of a larger scale and thus improves the accuracy of plotting.

7.3.2. Adjusted Data.—The graphical procedure of Sec. 7.3.1 is impractical when the observations are large. In such cases the range of variation in Y as X varies is large relative to the width of the acceptance band for a fixed X ; when the Y scale is contracted sufficiently to go on a sheet of reasonable size, the upper and lower boundaries of the acceptance region are pulled so close together that the chart becomes useless. A remedy for this is to replace the sum of the squares of the observations Y

* Formula (54) gives the minimum value of formula (55). Actually, it gives a value slightly below the minimum, because the minimum, which occurs when $X = UN(N-1)/(Nk^2 + N - 1)$, is $NU^2(N-1)/(Nk^2 + N - 1)$. If Y is as small as (54), it is impossible for X to be too large; this is illustrated in Fig. 1.5.

by the sum of the squares of adjusted observations Y' where

$$\begin{aligned} Y' &= \sum (x - A)^2 \\ &= Y - 2AX + NA^2 \end{aligned} \quad (71)$$

and A is an adjustment constant. The adjustment constant is, in effect, subtracted from each observation before squaring; actually the sum of squares of the adjusted observations, Y' , is obtained directly from X and Y by formula (71) without adjusting each observation.

In order to make the chart most useful, the adjustment constant A should, if possible, be chosen near the mean of the characteristic being inspected. Usually there will be some evidence as to the general neighborhood in which the mean lies. If there is no evidence at all, it will often be suitable to choose A somewhere in the interval between $U/(k^2 + 1)$ and U .

To compute Y' , X and Y are obtained simultaneously as described in Sec. 7.1, and X is recorded. Then X is copied to the keyboard and multiplied negatively by $2A$, which may be computed in advance. Next NA^2 , which also should be computed in advance, is added. These two operations adjust the sum of squares, and Y' may be copied from the lower dials. An alternative computing procedure, which may be useful if the same inspection plan, or at least the same adjustment constant, is to be used repeatedly, is to prepare a table showing $(x - A)^2$ for the various values of x that might be observed. From this table Y' can be found by simple addition.

The values of X and Y' determine whether the acceptance criterion has been met. If $X > NU$, immediate rejection may be made, according to formula (53). Instead of (54) for immediate acceptance, we have

$$Y' \leq \frac{(U - A)^2(N - 1)}{k^2 + 1} \quad (72)$$

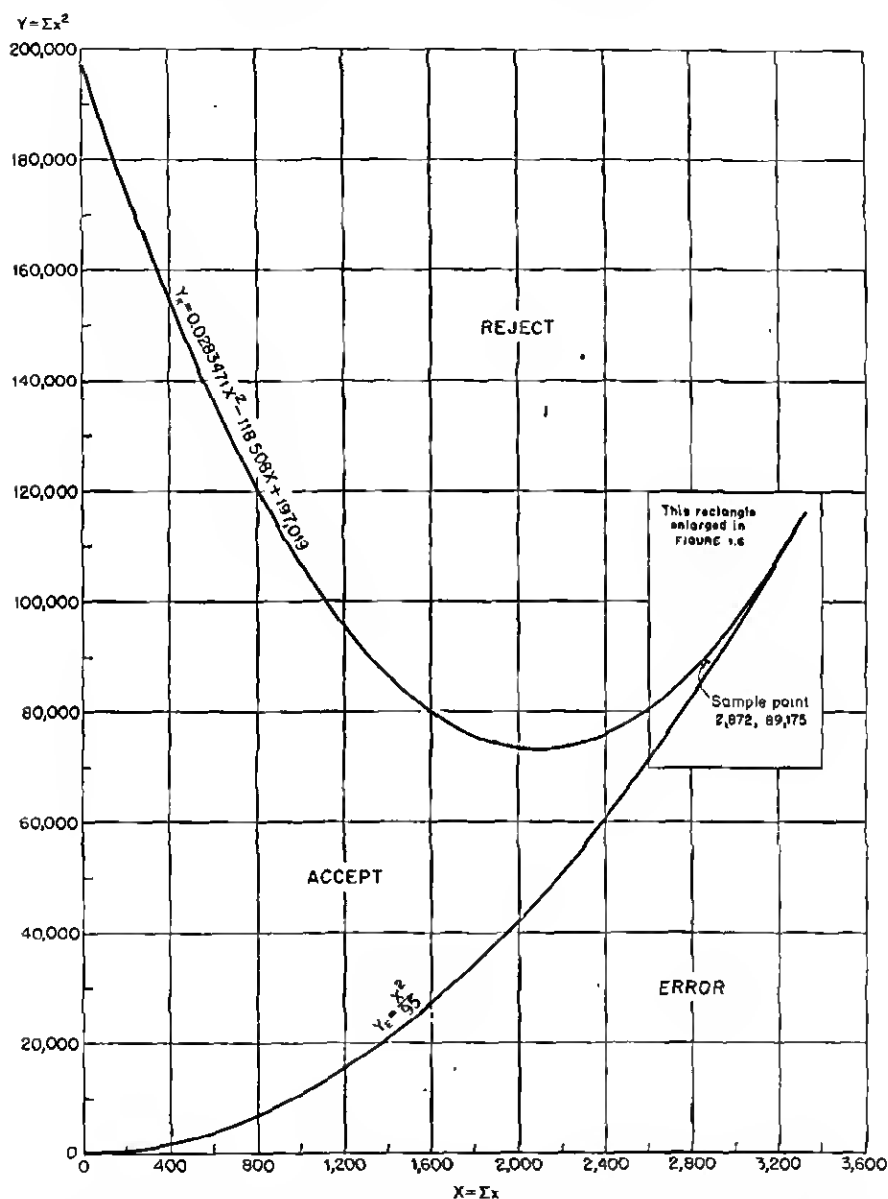
If this is fulfilled the lot may be accepted immediately. Notice that Y' may satisfy (72) even when Y fails to satisfy (54). Otherwise, a chart similar to Fig. 1.6 may be drawn in which the upper boundary of the acceptance region is given by

$$Y'_R = aX^2 - (b + 2A)X + (c + NA^2) \quad (73)$$

where a , b , and c are defined by (56), (57), and (58), and the lower boundary is given by

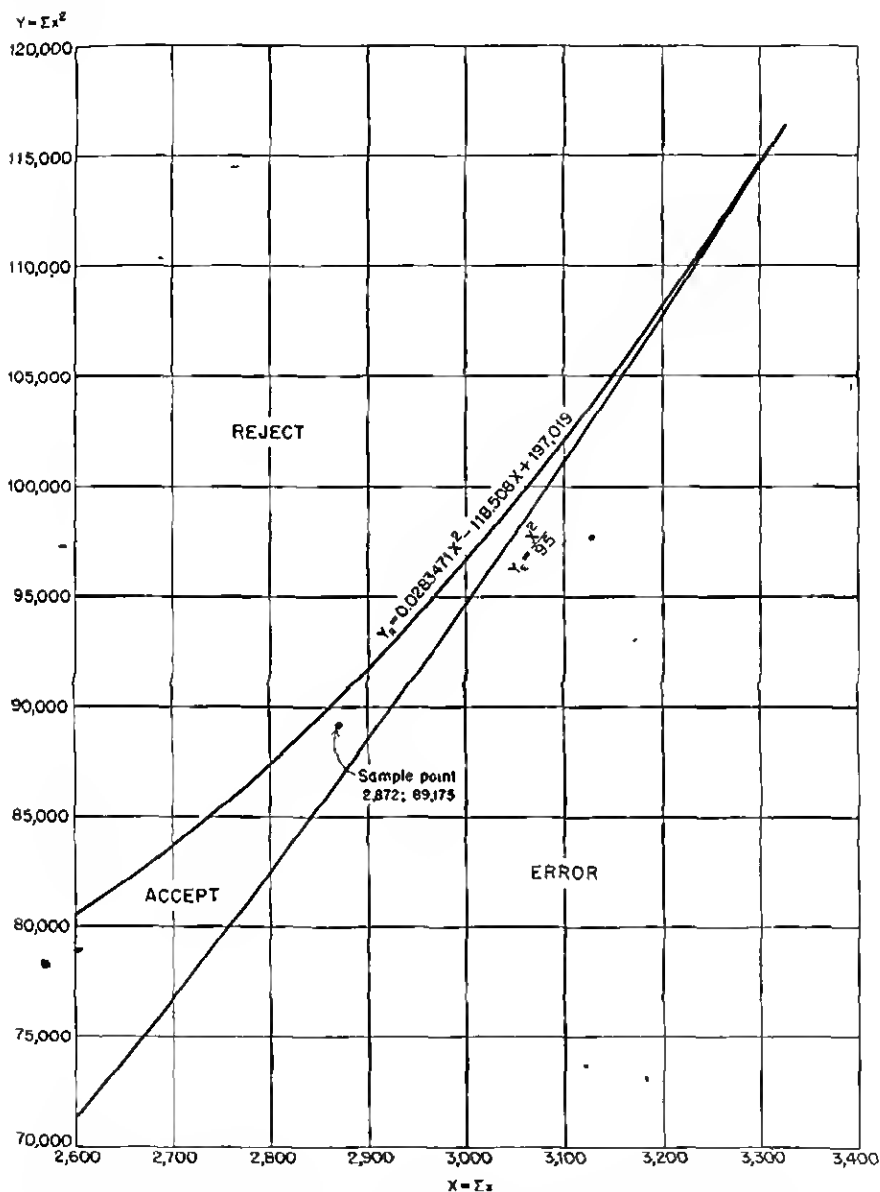
$$Y'_L = \frac{X^2}{N} - 2AX + NA^2 \quad (74)$$

Figure 1.7 shows such a chart for the example of Sec. 7.2.2, the adjustment constant being taken as $A = 30$. Thus, the equations of the



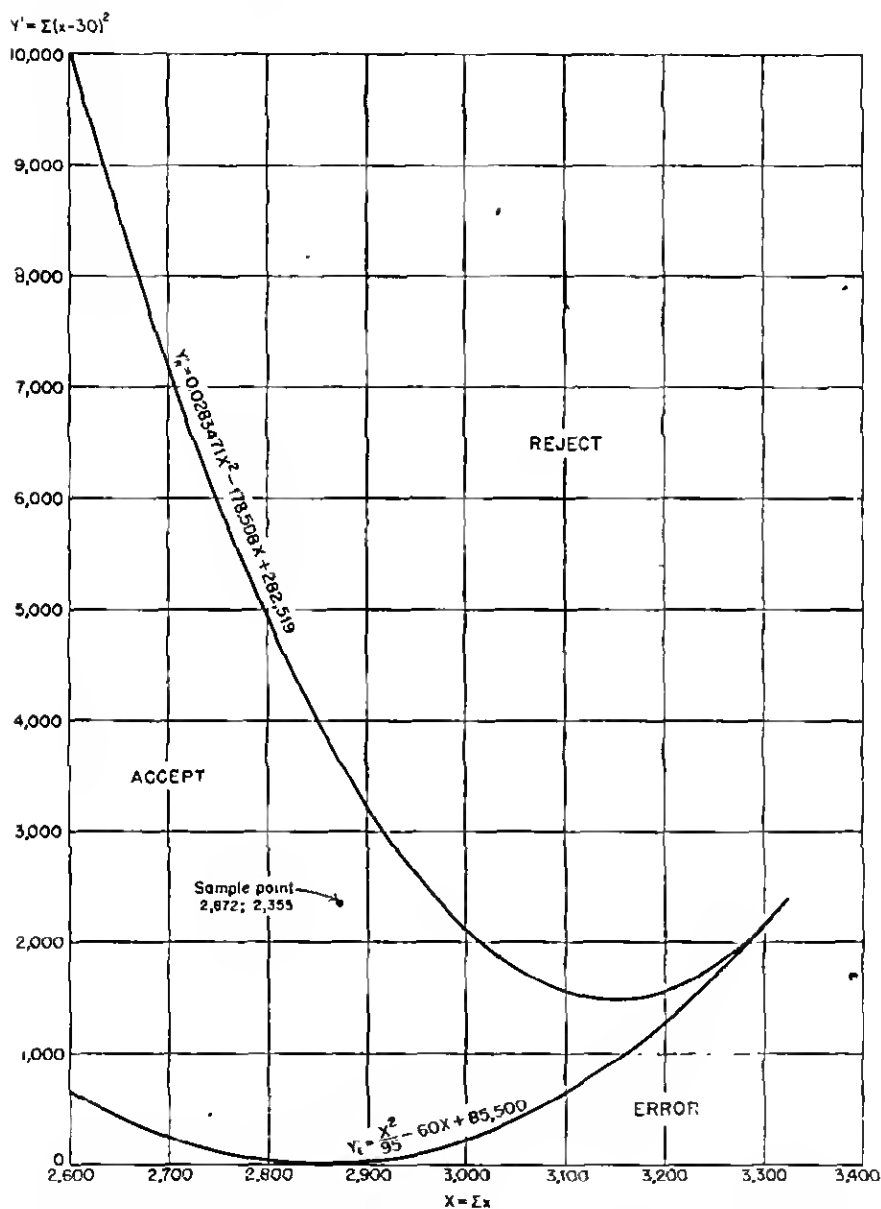
NOTE: The Y_E curve should extend indefinitely, separating the error and rejection regions, but in a small figure this would make it difficult to identify the termination point of the acceptance region.

FIG. 1.5.—Graphical procedure for determining from Σx and Σx^2 whether $\bar{x} + ks \leq U$; $N = 95$, $k = 0.7645$, $U = 35$.



NOTE: See note to Fig. 1.5.

FIG. 1.6.—Enlarged segment of computational chart in terms of original data (enlargement of area indicated in Fig 1.5).



NOTE: See note to Fig. 1.5.

FIG. 1.7.—Graphical procedure for determining from Σx and $\Sigma(x - A)^2$ whether $\bar{x} + ks \leq U$; $N = 95$, $k = 0.7645$, $U = 35$, $A = 30$.

upper and lower boundaries of the acceptance region are

$$Y'_R = 0.0283471X^2 - 178.508X + 282.519 \quad (75)$$

$$Y'_L = 0.0105263X^2 - 60X + 85.500 \quad (76)$$

Since $2A = 60$ and $NA^2 = 85,500$, the value of Y' in the sample is, by formula (71), 2,355. This does not satisfy inequality (72), which would require that Y' be 1,483 or less; but when the point $X = 2,872$, $Y' = 2,355$ is plotted in Fig. 1.7, it is seen to be within the acceptance region.

It is stated in Sec. 7.2.1 that (72) is more effective than (54) in permitting immediate acceptance. In the present example, (72) requires that $Y' < 1,483$, which (since $X = 2,872$) is equivalent to requiring that $Y \leq 88,303$, whereas (54) requires that $Y \leq 72,675$. Thus values of Y between 72,675 and 88,303 will lead to immediate acceptance by (72) but not by (54). From the point of view of permitting acceptance on the basis of Y' , rather than the point of view of making the chart usable, very nearly the most efficient form of (72) is obtained by setting

$$A = \frac{(1 + k^2)\mu' - U}{k^2} \quad (77)$$

where μ' is the best estimate of \bar{x} available before the sample is inspected. In the present example, if μ' is taken as 30, formula (77) shows A about 21.5. Taking $A = 21$, formula (72) becomes $Y' \leq 11,628$, and since the sample value of Y' is 10,146, immediate acceptance is possible. The value of A given by (77) may be made the basis of a condition for acceptance in terms of Y ; intermediate between (54) and (55), which are, respectively, constant and quadratic in X , the linear condition for acceptance may be inserted

$$Y \leq c' - b'X \quad (78)$$

where

$$b' = b - 2aN\mu' \quad (79)$$

$$c' = c - aN^2\mu'^2 \quad (80)$$

and a , b , and c are defined by (56), (57), and (58). Taking $\mu' = 30$ in the illustrative example, (78) becomes $Y \leq 90,468$, which leads to acceptance. If the value of μ' happens to coincide with \bar{x} , (78) becomes equivalent to (55).

8. REDUCED AND TIGHTENED INSPECTION

8.1. Purpose of Reducing or Tightening Inspection

It is emphasized in Secs. 3.4 and 6.1 that the OC curve shows the conditional probability that if a submitted lot has a given quality p it will be accepted. It does not show the probability that a lot of quality p will be accepted. This latter probability cannot be controlled

by the sampling plan alone, for it depends upon the probability that a lot of quality p will be submitted.

In judging the value of the protection afforded by a sampling plan, information about the quality of submitted material is important. The fact that a plan rejects 90 percent of submitted lots having a certain unacceptable quality may be of little importance if a great many of the submitted lots are of that quality; in that case many of the lots passed by the plan will be unacceptable, even though most of the submitted lots are rejected. The fact that the plan rejects 90 percent of submitted lots of an unacceptable quality p is also unimportant if submitted lots rarely have that quality, for then very little such material will be accepted, even though most submitted lots are passed. In the first case, when bad material is submitted very often, the protection given by the sampling plan may be inadequate and require tightening; but in the second case, when bad material is rarely submitted, the protection may be superfluous and reduction may be permissible.*

8.2. Criteria for Reducing or Tightening Inspection

8.2.1. Process Average Percent Defective.—The principal criterion for determining whether reduced inspection is permissible or tightened inspection necessary is the process average percent defective, usually called simply the process average or PA, which is an estimate of the percent defective computed from a number of lots.

This estimate is best stated as a confidence interval, that is, an interval within which it may be asserted with, say, 95 percent confidence that the true process average lies. If the estimate were stated as a single figure, it would invariably differ from the true process average because of sampling fluctuations; and the question would therefore arise as to whether the difference between the estimated process average and the acceptable quality level could reasonably be ascribed to sampling fluctuations, or whether on the other hand it indicated a real discrepancy between the true process average and the acceptable quality level. A confidence interval answers such questions. It is constructed from the sample data in such a way that 95 percent, or any other desired proportion γ , of the samples will lead to confidence intervals that overlap the true process average.

For the purpose of computing the process average, all data in the samples from a number h of consecutive lots are thrown together into one large sample. The mean \bar{x} and the standard deviation s of this combined sample are computed from formulas (4) and (6). Alternatively, they

* For a general discussion of the principles and methods of tightening and reducing inspection, see Statistical Research Group, *Sampling Inspection*. The discussion there relates to inspection by attributes, but, insofar as it runs in terms of the OC curve and the amount of inspection, it is also applicable to variables.

may be computed from the means \bar{x}_i , the standard deviations s_i , and the sample sizes N_i of the individual samples by the following formulas:

$$\bar{\bar{x}} = \frac{N_1\bar{x}_1 + N_2\bar{x}_2 + \cdots + N_h\bar{x}_h}{N_1 + N_2 + \cdots + N_h} = \frac{\sum N_i\bar{x}_i}{N} \quad (81)$$

$$s^2 = \frac{(N_1 - 1)s_1^2 + (N_2 - 1)s_2^2 + \cdots + (N_h - 1)s_h^2 + N_1(\bar{x}_1 - \bar{\bar{x}})^2 + N_2(\bar{x}_2 - \bar{\bar{x}})^2 + \cdots + N_h(\bar{x}_h - \bar{\bar{x}})^2}{N_1 + N_2 + \cdots + N_h - 1} \quad (82)$$

$$= \frac{\sum(N_i - 1)s_i^2 + \sum N_i\bar{x}_i^2 - \frac{(\sum N_i\bar{x}_i)^2}{N}}{N - 1}$$

where

$$N = \sum N_i \quad (83)$$

From $\bar{\bar{x}}$, s , and U we compute k_o , the observed difference between U and the sample mean in units of the sample standard deviation

$$k_o = \frac{U - \bar{\bar{x}}}{s} \quad (84)$$

Then, given a confidence coefficient γ , a confidence interval which in a fraction γ of samples will overlap the true fraction defective may be obtained from formulas (42) and (43) by substituting k_o for k and $(1 - \gamma)/2$ for L_p . The p and p' given by (42) and (43) are the upper and lower confidence limits \hat{p}_γ and \check{p}_γ , respectively, for the fraction defective produced by the process. The larger the confidence coefficient, the broader the interval; and the smaller the confidence coefficient, the narrower the interval. In fact, if γ is 1, the interval runs from 0 to 100 percent; and if γ is 0, the interval includes only the point $p = \bar{p}$, where \bar{p} is the probability that a normal deviate will exceed k_o .

If the acceptable quality level lies above the confidence interval, reduced inspection is permissible.* If it lies below the confidence interval, tightened inspection is necessary. If it lies within the confidence interval, normal inspection may be continued.

In order to avoid too frequent shifts in the degree of inspection, it is advisable that the criteria for resuming normal inspection when tightened or reduced inspection is in effect should differ from the criteria for remaining on normal inspection when it is already in effect. One way to achieve this is to use a larger confidence coefficient when deciding whether to continue normal inspection than when deciding whether to resume nor-

* For reduced inspection, it is customary to impose a further requirement to restrict the variability of the process average from lot to lot. This usually takes the form of requiring that each of the last twenty (or some other number) lots have been acceptable.

mal inspection. Reduced inspection, for example, will be installed as soon as the process average falls to a certain level, but once it has been installed normal inspection will not be resumed unless this level is exceeded by a certain margin. It is therefore possible, once either reduced or tightened inspection has been installed, to continue it under conditions that would not justify its introduction were normal inspection in effect.

8.2.2. Illustrative Computation of Process Average.—Suppose that the combined sample from several inspection lots contains 95 observations, that their sum is 2,872, that the sum of their squares is 89,175, and that values above 35 represent defects. Suppose a confidence coefficient γ_c of 0.99 is used for judging whether to continue normal inspection and a confidence coefficient γ_r of 0.95 for judging whether to resume normal inspection. Thus

$$N = 95 \quad \Sigma x = 2,872 \quad \Sigma x^2 = 89,175 \quad (85)$$

$$U = 35 \quad \gamma_c = 0.99 \quad \gamma_r = 0.95 \quad (86)$$

Then, from formulas (4) and (6)

$$\bar{x} = 30.2316 \quad s = 5.000 \quad (87)$$

so

$$k_o = \frac{35 - 30.2316}{5} = 0.9537 \quad (88)$$

Entering Table 1.5 with $K_c = 0.9537$, we find (by linear interpolation) 17.01 percent as the point estimate \hat{p} , corresponding with a confidence coefficient of zero, of the process average percent defective.

To find the 99 percent confidence limits, we substitute $k = 0.9537$, $L_p = (1 - 0.99)/2 = 0.005$ into (42) and (43). The details of a similar computation are shown in Sec. 6.3.1. The 99 percent confidence limits are

$$\hat{p}_{0.99} = 10.15 \text{ percent} \quad \text{and} \quad \hat{p}_{0.99} = 26.29 \text{ percent} \quad (89)$$

Similarly, taking $L_p = 0.025$, the 95 percent confidence limits are

$$\hat{p}_{0.95} = 11.57 \text{ percent} \quad \text{and} \quad \hat{p}_{0.95} = 23.86 \text{ percent} \quad (90)$$

If normal inspection is in effect, it will be continued if the AQL for the product is between 10.15 and 26.29 percent defective; reduced inspection will be installed if the AQL exceeds 26.29 percent and tightened inspection will be installed if the AQL is below 10.15 percent. If tightened or reduced inspection is in effect, normal inspection will be resumed if the AQL is between 11.57 and 23.86 percent. If the difference between the intervals for continuation and for resumption is too small, that is, if too many shifts occur, it can be widened by increasing the difference between the two confidence coefficients used.

For routine operations in which the same AQL and the same value of U are to be used repeatedly, it is desirable to prepare a table showing for various sample sizes the values of k_c that result in continuing normal inspection if it is in use and those that result in resuming normal inspection if tightened or reduced inspection is in use. In the present illustration, for example, if the AQL is 15 percent, a value of k_c computed from 95 observations leads under normal inspection to continuing normal inspection if it lies between $\hat{k}_{0.99} = 0.7380$ and $\hat{k}_{0.99} = 1.4107$, or leads under reduced or tightened inspection to resuming normal inspection if it lies between $\hat{k}_{0.95} = 0.8048$ and $\hat{k}_{0.95} = 1.3113$. These values are determined from formula (21), using both the plus and the minus signs to obtain upper and lower limits and taking $p_1 = \text{AQL}$, $\alpha = (1 - \gamma)/2$. An example of the computation of (21) is given in Sec. 4.5.2.

8.3. Methods of Reducing or Tightening Inspection

Reduced inspection may be achieved by reducing N , perhaps as much as 40 or 50 percent, and adjusting k so that the producer's risk will not be increased. This leaves the OC curve approximately unchanged for qualities equal to or better than the AQL but increases the risk that lots of worse quality will, if submitted, be accepted.

Tightened inspection may be achieved by increasing k but leaving N fixed. This moves the OC curve to the left, thus reducing the consumer's risk but increasing the producer's risk.

9. CHOICE OF QUALITY STANDARDS AND EVALUATION OF PROPOSED SAMPLING PLANS

9.1. General Discussion

The definition of a defective item, the choice of an AQL and an LTPD,* and the selection of producer's and consumer's risks usually require a compromise between what is technically or economically desirable in the use for which the product is intended and what is technically or economically feasible in its production. Although no fixed rules can be established for selecting U , p_1 , p_2 , α , and β , a few guides are worth noting.

* LTPD, or lot tolerance percent defective, is defined sometimes in terms of the use for which the product is intended, as the worst quality for which there should be any appreciable probability of a lot's being accepted, and sometimes, in terms of the sampling plan, as that quality for which the probability of acceptance has a specified value (customarily 10 percent). Similarly, the AQL, or acceptable quality level, is defined sometimes as the worst quality that can be consistently accepted or as the best quality for which there should be any appreciable probability of a lot's being rejected, and sometimes, as that quality for which a certain sampling plan gives a specified probability of rejection (customarily 5 percent). We follow the definitions in terms of sampling plans, using the customary risks of 5 and 10 percent for the AQL and LTPD, respectively.

Some of these five quantities can be selected arbitrarily or by convention without restricting the range of available plans. For example, it is more or less conventional to take the producer's risk α as 5 percent and the consumer's risk β as 10 percent. Then the AQL, or p_1 , may be defined as that quality for which the probability of acceptance should be 95 percent and the LTPD, or p_2 , as that quality for which the probability of acceptance should be 10 percent. Sometimes α and β are set tentatively and values of U , p_1 , and p_2 selected; then the values of α and β may be reexamined in the light of the number of lots of qualities p_1 and p_2 likely to be submitted and the costs of rejecting those of quality p_1 or accepting those of quality p_2 .

To select a sampling plan, two independent analyses should be made and their results merged. One study should consider the uses to which the product is to be put. What is required of each item, how rigid are these requirements, and what is the effect of a certain percentage of the items failing to meet the requirements? The other study should consider the production process. Within what limits do most of the items fall, how stable are these limits, what would be the costs of improving them, and what is the cost of having a lot rejected? In designing a sampling plan on the basis of these two studies, it is necessary to take into account the cost of inspection. What is the cost of drawing a sample, what is the cost of inspecting the items, what is the cost of analyzing the data, and how do all these vary with the size of the sample?

9.2. Analysis of Production Possibilities

It should be assumed that the producer will consider the OC curve as in effect the specification of what will be accepted, and that he will adjust his operations to an OC curve as best suits his own circumstances. For example, if the producer finds that a rejected lot entails considerable costs, he will consider that the given OC curve actually forces him to produce at a quality much better than the AQL, how much better depending upon how sharply the cost of production rises and the probability of a rejection declines as quality improves. If improvements in quality are also costly, a given OC curve may mean that the consumer will receive—and, of course, ultimately pay for—better quality than he needs. Under such circumstances the consumer will find it advantageous to increase the amount of inspection, for which also he ultimately pays; this will steepen the OC curve, that is, increase the rate at which the probability of a rejection declines as quality improves, and therefore reduce the degree to which the producer is forced to improve the quality and raise the cost.*

There is obviously a relation between U on the one hand and p_1

* Some discussion of this point is given in J. Przyborowski and H. Wilénski, "Testing Clover Seed," especially Sec. III(b), pp. 281-285.

and p_2 on the other. If U is set very high, only very bad items are considered defective; only a small percentage of such items can be accepted, so p_1 should be small. If U is set very low, items are considered defective when they deviate very little from normal; the effect of such items is less serious, so a larger percentage of them can be accepted.

If we regard U as fixed, we may, by analyzing data on the quality characteristic that is to be inspected, estimate what proportion defective is being produced. Section 8.2 gives a method for finding confidence intervals \hat{p}_γ to \hat{p}_γ which, in a proportion γ of the samples from which such confidence intervals are computed, overlap the true fraction defective; or, if the confidence coefficient is reduced to zero, we may obtain a single-valued estimate \bar{p} . The height of the OC curve over the interval \hat{p}_γ to \hat{p}_γ then indicates approximately how much of the current production would be passed by a proposed sampling plan.

If, on the other hand, we regard p_1 as fixed, we may estimate the value of U necessary to give a confidence γ that the fraction defective will not exceed p_1 . This value is

$$\hat{U}_\gamma = \bar{x} + k_\gamma s \quad (91)$$

where k_γ is given by formula (21), using the plus sign and taking p_1 as the fixed fraction defective and α as $1 - \gamma$. Thus, in the example of Sec. 8.2.2, where $p_1 = 0.15$, $\bar{x} = 30.232$, and $s = 5.000$, $\hat{k}_{0.95} = 1.2632$ and $\hat{k}_{0.99} = 1.3695$; so we may be 95 percent confident that under the conditions prevailing when the sample was collected at least 85 percent of the items lie below $\hat{U}_{0.95} = 36.54$, or 99 percent confident that at least 85 percent lie below $\hat{U}_{0.99} = 37.08$. \hat{U} is called a "tolerance limit."*

9.3. Analysis of Consumption Requirements

In analyzing the consumption, or design, requirements of a product, account should be taken of the variability of other products or methods with which it will be associated in use. A discussion of this is beyond the scope of this chapter,† but one especially simple example may be mentioned.

* See Chap. 2 for a discussion of tolerance limits. Chapter 2, however, is concerned with two-sided tolerance limits, that is, values of k such that at least a given proportion P of the population is included between the limits $\bar{x} - ks$ and $\bar{x} + ks$.

An excellent discussion of tolerance limits, which in fact is the original source from which subsequent theoretical work has developed, is given in Shewhart, *Statistical Method*, Chap. II, pp. 50-79, *How Establish Limits of Variability?*

† See Shewhart, *Economic Control of Quality*, Part V, pp. 247-272, *Statistical Basis for Specification for Standard Quality*, especially Chap. XVII, pp. 249-261, *Design Limits on Variability*, in which Sec. 5, pp. 252-256, considers *Tolerances for Quality of Finished Product in Terms of Tolerances of Piece-parts*, and Sec. 6, pp. 256-259, discusses *The General Problem of Setting Tolerances on Controlled Product*.

Suppose the items from a lot are to be assembled at random in sets of n , and a set of n will be defective if the sum of the lengths of the n pieces exceeds nU' , that is, if the mean length in the set exceeds U' . If we consider lot quality measured by the percent of means of n that exceed U' and select two points on the desired OC curve, values of N and k , say N' and k' , can be obtained from (10) and (11) or (12). If now inspection is carried out on the basis of individual items, rather than sets of n , the lot can be accepted if in a sample of nN' items

$$\bar{x} + \frac{k'}{\sqrt{n}} s \leq U' \quad (92)$$

where \bar{x} and s are the mean and standard deviation computed from the nN' items.

If in this example a piece were considered defective if it exceeded one- n th the allowable sum for n pieces, that is, if it exceeded U' , the sampling plan would require a sample of N' items and the acceptance requirement would be

$$\bar{x} + k's \leq U' \quad (93)$$

This would necessitate production at a higher quality than would (92). For example, if $n = 4$ and $k = 0.7645$, the indifference quality, that is, the quality having an equal chance of acceptance or rejection, is 35.12 percent defective for (92) and 22.23 percent for (93). If $n = 9$ and $k = 2.0077$ (the k given in Table 1.2 for $p_1 = 0.015$, $p_2 = 0.03$), the indifference quality is 25.17 percent under (92) and 2.23 percent under (93).

As a digression, it may be observed that averages in sets of n may be appropriate measures of quality when inspection is undertaken to determine whether full measure is delivered. Suppose tomato juice is packed in one-gallon cans* that the final purchasers buy one at a time. Then any purchaser whose can contains less than one gallon is cheated, whether or not some other purchaser receives an equivalent or even a greater excess. Even though the purchaser would not be cheated in the long run if his purchase were repeated frequently, an appreciable shortage in any one can may inconvenience or annoy him—in fact, may prevent his repeating the purchase. In such circumstances, the appropriate measure of lot quality is the percent of cans containing less than a stated amount, say one gallon, or perhaps 0.99 gallon if a 1 percent deviation is permissible. If, however, the tomato juice is to be sold to restaurants in cases of 12 cans, the appropriate measure of lot quality is the percent of groups of 12 that average less than one gallon per can. If the tomato juice is to be sold to Army camps in carloads, the percent of carloads

* The example is taken from Peach, *Industrial Statistics*, p. 86. Peach, however, treats the example differently.

averaging less than one gallon per can is the appropriate measure of lot quality; in such a case, however, one earload might well be an inspection lot, so that the lot mean would become the appropriate quality measure.

9.4. Normality Assumption

If within lots the distribution of items is not approximately normal, the sampling plan usually controls the percent defective as consistently as if the distribution were normal, but not at the level intended.

What the plan actually controls is the quantity defined by equation (1), namely,

$$K = \frac{U - \mu}{\sigma} \quad (94)$$

Thus a lot is rejected if the sample value of K , say k_o , is too small and accepted if it is sufficiently large. The OC curve might be plotted with the horizontal axis representing the true value of K in submitted lots; such an OC curve would be essentially correct regardless of the normality of the distribution within lots. The assumption of normality becomes important when translating values of K into values of p , the fraction defective.

If the distribution is not normal but its *form* is stable from lot to lot and is such that the percent defective is determined by K , then it is possible to substitute for Table 1.5 another table more appropriate for translating K into percent defective. In any event, it may be assumed that the fraction defective corresponding with any K does not exceed $(1/K)^2$; and if the distribution is unimodal and has its mode near its mean it may be assumed that for any K the fraction defective does not exceed $(2/3K)^2$.*

The effects of non-normality are excellently stated by Jennett and Welch:†

The above theory is developed on the assumption that the parent population sampled is Gaussian. Even if it is not, the reasoning relating the distribution of k_o with K will not be invalidated unless the samples are very small, because non-normality will not have much influence on \bar{x} and s . The chief error lies in connecting K with p by using the normal tables. This can be obviated if some other constant distributional form can be assumed for which the relation between the standardized deviate K and p is known. If we could say that the distribution would maintain the same shape . . . , although with possible changes in the mean and standard deviation, the above theory would need little modification.

* These quantities are based on the Techebycheff and Camp-Meidell inequalities, respectively (see SHEWHART, *Economic Control of Quality*, pp. 176-177); in the present context they can be halved if symmetry can be assumed, and reduced further if positive skewness is assumed.

† "The Control of Proportion Defective." The passage quoted is from Sec. 3, p. 88, Effect of Non-normality. The notation in the passage as quoted has been altered to agree with that used in this chapter.

It would be misleading, however, to lay too much emphasis on the necessity for making the connection between K and p correctly. Usually it is not possible to say with *absolute certainty* that a particular value of p is satisfactory and another, differing little from it, is unsatisfactory. Indeed, often it may not be clear that p has any intrinsic importance at all, but it may still be useful for purposes of control. For the same reason K may be regarded as a useful feature of the distribution to aim at controlling, without inquiring too closely into the exact meaning of K . Non-normality is therefore not such a serious matter as it may appear. However, no final word can be said about this without reference to the context in which the method is to be used.

10. SIMULTANEOUS USE OF SEVERAL SAMPLING PLANS

10.1. Inspection of Several Quality Characteristics

Often the quality of an item depends upon several variables. There may be measurements of physical dimensions, for example, those which determine whether the item will fit properly in a final assembly, or whether full measure has been delivered; measurements of the properties of the item, for example, hardness, chemical composition, tensile strength, or modulus of elasticity; measurements of performance, for example, duration of useful life or rate of output; and so forth. The lot quality then is measured by n fractions defective, say p_1, p_2, \dots, p_n .

Suppose that n criteria of the form

$$\bar{x} + ks \leq U \quad (95)$$

are applied to a single sample of N . The probability that the lot will pass all n tests cannot be read from the OC curve for any one test. For a given set of values p_1, p_2, \dots, p_n , the probability that a lot will be accepted cannot be more than the smallest among the n values of L_p ; it will be this large if, and only if, the n tests are perfectly correlated, so that a lot passing any one test is certain to pass all. At the other extreme, the probability of acceptance may be zero; it will be this small if a lot that passes one test is certain to fail some other, or if L_p is zero for any of the n values of p .*

* It might be thought that these two extreme cases would never be encountered in practice. Specification writing and acceptance test designing being what they are, this is not the case. The author cherishes the memory of one particular specification for a cylindrical tube. It specified length, inside diameter, outside diameter, concentricity, weight, density, absence of voids, and all the details of chemical composition, physical properties, and manufacturing processes that determine density. Such a specification must be, at least in some degree, either redundant or inconsistent; this particular one perhaps had been redundant originally, but through an encrustation of changes made in one detail at a time it had become inconsistent. It would be naive to assume, however, that because no material could meet the acceptance criteria none was accepted. On the contrary, all of it was accepted. This was achieved partly by the buyer's reasoning that the product was needed, that the acceptance tests failed to pass usable material, and that therefore material failing to pass the tests was usable;

Between these two extremes of perfect positive correlation and perfect negative correlation among the tests is the case in which the tests are independent. In this case, the probability of accepting a lot of quality p_1, p_2, \dots, p_n is given by the product of the individual probabilities of acceptance:

$$L_{p_1, p_2, \dots, p_n} = L_{p_1} \cdot L_{p_2} \cdot \dots \cdot L_{p_n} \quad (96)$$

Since each L_{p_i} is 1 or less, this product is less than the least L_{p_i} among the set of n . If $n = 3$ and each $L_{p_i} = 0.95$, the product is $(0.95)^3$ or 0.857; if each $L_{p_i} = 0.99$, the product is $(0.99)^3$ or 0.970. For $n = 10$ the corresponding products are 0.599 and 0.904. (When L_{p_i} is near 1 and n is not too large, the probability of rejecting is about n times as large for n independent tests as for one.)

Sometimes the situation is that for good quality the various tests are independent but that for poor quality the tests are positively correlated. Thus, if for each of five characteristics a lot has fractions defective that give it a 95 percent chance of acceptance on the individual tests, its chance of passing all five tests is about $(0.95)^5$ or 0.774. But if its chance of acceptance on each individual test is 0.10, its chance of acceptance on all five may be nearly 0.10. In such situations, not only is the OC curve for the battery of tests lower than that for any one test, but it gives less sharp discrimination between good and bad lots. On the other hand, if the tests are independent or positively correlated for good quality but negatively correlated for bad quality, the discrimination is sharpened.

Another aspect of the simultaneous use of several criteria like (95) is that this treats the various tests on an attribute basis, so to speak. If a lot just barely fails to pass one test but appears to be of exceptionally high quality on all other tests, it is rejected; whereas a second lot that just barely passes each test is accepted. It would be preferable to combine all the measurements on one item into a single score for that item and judge the lot by the scores of the sample items.*

All these uncertainties about the simultaneous operation of several criteria make the selection, operation, and interpretation of the plan much less clear-cut and straightforward than when only one criterion is con-

and partly by the seller's disclaiming responsibility for the quality of the product, reasoning that he could take responsibility either for the quality of the product or for following detailed instructions for making it, but not for the consistency of those instructions with the desired quality.

* Chapter 3 deals with this problem. The methods presented there are new and have not yet been used extensively or developed to the point where they are comparable with those of this chapter in simplicity of selecting plans and constructing OC curves, or in ease of routine operation and interpretation. They will nevertheless well repay careful study, especially when complicated and expensive products or experiments are concerned.

cerned. They underscore the necessity, if variables are to be used, of a careful preliminary analysis of a rather large body of data on the product to which the plans are to be applied.

10.2. Upper and Lower Bounds on a Single Quality Characteristic

10.2.1. General Considerations.—The OC curve for two simultaneous criteria of the form (96) can be determined mathematically in the case where the two criteria simply impose upper and lower limits on a single characteristic; that is, the case where an item is defective if it is either above some upper limit U or below some minimum M . Some mathematical investigations of this have been made,* but no completely satisfactory solution has yet been obtained. The indications are, however, that for practical purposes it will ordinarily suffice to use two criteria of the form (96) determined independently for the upper and lower limits. Two points about this procedure, however, should be recognized.

The first point is that the combinations of \bar{x} and s that lead to acceptance are not quite the same when two one-sided criteria are used as they would be if a single two-sided test were constructed. The combinations that lead to acceptance with two one-sided tests (having the same values of N and k) are included in an area shaped like the triangle of Fig. 1.8, whereas a single two-sided test would result in rounding off the top corner of this triangle, somewhat as in the curve of Fig. 1.8. If most of the production should fall in the small area not common to both regions, this difference would be of importance. This would be a situation in which the mean behaved excellently, consistently lying midway between M and U , but the standard deviation was continually near the maximum value permitting acceptance with the best value of the mean. If such a situation were to prevail consistently, acceptance inspection would probably be based on the standard deviation alone.

The second point to be kept in mind in using two one-sided tests for a given characteristic is the effect on the OC curve. The true OC curve for a two-sided test cannot be expressed in terms of the lot fraction defective alone; it depends upon the lot mean and standard deviation. A sample that fails to meet one criterion because of a large standard deviation is likely to fail the other criterion also; but a sample that fails one criterion because of an extreme mean is likely to pass the other criterion.

Thus, although the use of two one-sided criteria to control both upward and downward variation often works out satisfactorily in practice, it should be recognized as an improvisation for a problem that is in essential respects different from the one-sided problem and is less amenable to simple methods and interpretations.

* The mathematical work was done in the Statistical Research Group by A. Wald and J. Wolfowitz but has not been published.

10.2.2. Use of a Pair of One-sided Criteria.—Suppose two tests are constructed so that with one the probability is β that a lot with fraction p ($p < 0.5$) above U will be accepted and with the other the probability is β that a lot with fraction p below M will be accepted. If the standard deviation of the measurements is small, the probability is practically β that a lot with fraction p outside the limits M and U will be accepted; but if the standard deviation is large, the probability is practically β that a lot with fraction $2p$ outside the limits M and U will be accepted. If $p/2$ is substituted for p , the test will give the intended probability of acceptance for high values of the standard deviation but not for low values of the standard deviation.

If the standard deviation is expected always to be low—it need not be so low when the relevant values of p are small as when they are large—or if lots with high standard deviations are sufficiently infrequent as to have only negligible effects on the operation of the tests, a pair of one-sided tests may be used successfully. The two acceptance criteria, both of which must be satisfied before a lot is accepted, are then

$$\bar{x} + ks \leq U \quad \text{and} \quad \bar{x} - ks \geq M \quad (97)$$

It may be noted that if $\bar{x} > (M + U)/2$, the second inequality can be ignored, for it will surely be met if the first is; similarly, if $\bar{x} < (M + U)/2$, the first inequality can be ignored.

As in the case of a single criterion, we may note that if

$$X > NU \quad \text{or} \quad X < NM \quad (98)$$

the lot may be rejected without regard to Y , where X and Y are the sum of the observations and the sum of the squares of the observations, respectively, as defined by formulas (51) and (52).

Second, we may note that if

$$Y \leq \frac{U^2(N-1)}{k^2+1} \quad \text{and} \quad X \geq N \frac{M+U}{2} \quad (99)$$

the lot may be accepted.

Third, if neither (98) nor (99) is satisfied, the lot is accepted if

$$X \geq N \frac{M+U}{2} \quad \text{and} \quad Y \leq aX^2 - b_U X + c_U \quad (100)$$

or

$$X \leq N \frac{M+U}{2} \quad \text{and} \quad Y \leq aX^2 - b_M X + c_M \quad (101)$$

where

$$a = \frac{Nk^2 + N - 1}{N^2k^2} \quad (102)$$

$$b_U = \frac{2U(N-1)}{Nk^2} \quad b_M = \frac{2M(N-1)}{Nk^2} \quad (103)$$

$$c_U = \frac{U^2(N-1)}{k^2} \quad c_M = \frac{M^2(N-1)}{k^2} \quad (104)$$

If neither (100) nor (101) is met, the lot is rejected.

For adjusted observations, as defined by (71), the lot may be accepted without regard to X if

$$Y' \leq \frac{(U+A)^2(N-1)}{k^2+1} \quad \text{when} \quad A \geq \frac{M+U}{2} \quad (105)$$

or

$$Y' \leq \frac{(A-M)^2(N-1)}{k^2+1} \quad \text{when} \quad A \leq \frac{M+U}{2} \quad (106)$$

In place of (100) and (101) we have

$$X \geq N \frac{M+U}{2} \quad \text{and} \quad Y' \leq aX^2 - (b_U + 2A)X + (c_U + NA^2) \quad (107)$$

$$X \leq N \frac{M+U}{2} \quad \text{and} \quad Y' \leq aX^2 - (b_M + 2A)X + (c_M + NA^2) \quad (108)$$

The most efficient form of (105) and (106), either for graphical purposes or for permitting immediate acceptance on the basis of Y' alone, is obtained by setting

$$A = \frac{M+U}{2} \quad (109)$$

In this case inequalities (105) and (106) are identical.

For either adjusted or unadjusted observations graphs may be constructed as described in Sec. 7.3. The maximum value of Y for acceptance for each value of X will be obtained from formula (100) or (107) for values of X greater than $N(M+U)/2$ and from formula (101) or (108) for values of X less than $N(M+U)/2$. In the case of adjusted observations, if $A = (M+U)/2$ the figures will be symmetrical about the line $X = NA$. The upper boundaries of the error region may be found by formula (70) or (74) of Sec. 7.3.

10.2.3. Two-sided Criterion.—A two-sided criterion is most easily applied if expressed in terms of a chart similar to Fig. 1.8, in which values of \bar{x} are represented horizontally and values of s vertically. For each sample, a point is plotted corresponding to the observed \bar{x} and s . If this point lies within the region bounded by the acceptance curve and the horizontal axis, the lot is accepted; otherwise, it is rejected.

The first step in finding the boundary of the acceptance region is to compute k and N from formulas (10) and (11). The values of p_1 and p_2 now represent fractions outside the interval M to U , instead of fractions above U .

The second step is to find the indifference quality p_0 , which is simply the probability that a normal deviate will exceed k . It may be determined from Table 1.5.

The third step is to divide p_0 arbitrarily into two parts, p'_0 and p''_0 ($p'_0 \leq p''_0$) such that

$$p'_0 + p''_0 = p_0 \quad (110)$$

Each pair p'_0, p''_0 leads to two points on the acceptance curve, so enough different pairs should be used to permit plotting the curve.

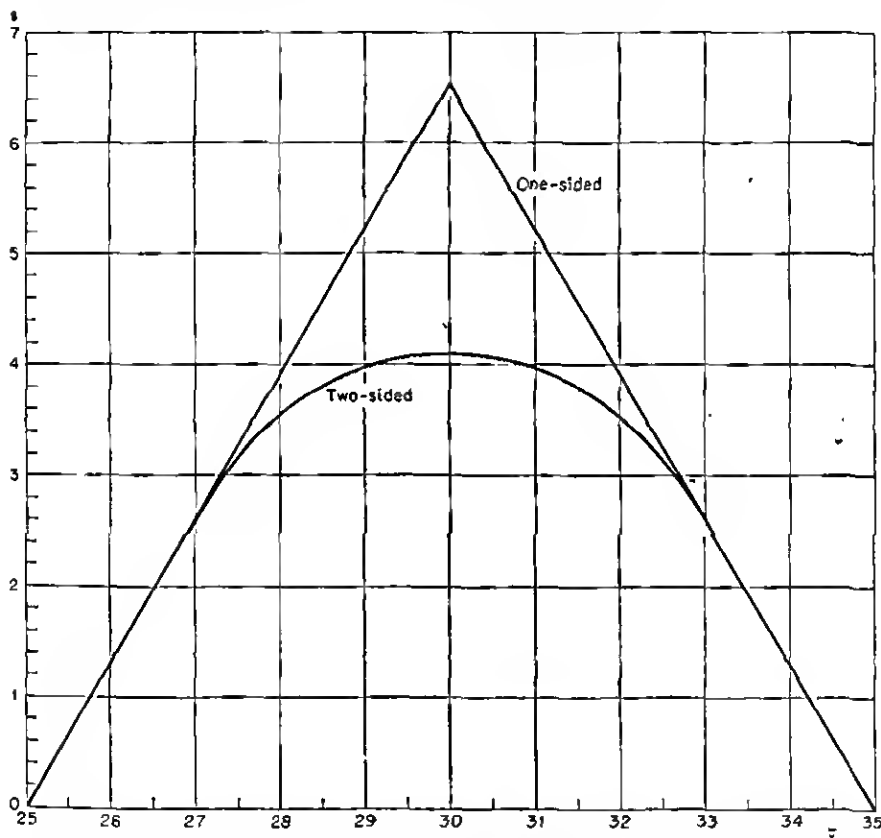


FIG. 1.8.—Acceptance region for a two-sided test defined by: $p_1 = 0.15$, $p_2 = 0.30$, $\alpha = 0.01$, $\beta = 0.02$, $U = 35$, and $M = 25$; also corresponding region for a pair of one-sided tests. [Data from Table 1.7, columns (9), (10) and (11).]

The fourth step is to find $K_{p'_0}$ and $K_{p''_0}$, normal deviates exceeded with probabilities p'_0 and p''_0 , respectively. These may be obtained from Table 1.1.

The fifth step is to substitute each pair of values $K_{p'_0}$, $K_{p''_0}$ into the pair of equations

$$\bar{x} = \frac{UK_{p'_0} + MK_{p''_0}}{K_{p'_0} + K_{p''_0}} \quad s = \frac{U - M}{K_{p'_0} + K_{p''_0}} \quad (111)$$

TABLE 1.7
COMPUTATION OF BOUNDARY OF ACCEPTANCE REGION FOR A TWO-SIDED TEST DEFINED BY $p_1 = 0.15$, $p_2 = 0.30$, $\alpha = 0.01$, $\beta = 0.02$,
 $U = 35$, $M = 25$ ($k = 0.7645$; $p_0 = 0.2223$)

p'_0	p'_0	$K_{p'_0}$	$K_{p'_0}$	$(3) + (4)$	$(3) - (4)$	$(6) \div (5)$	$2 \div (5)$	$\bar{x} = \frac{U+M}{2} + \frac{U-M}{2}$	$z' = U + M - (9)$	$s = \frac{U-M}{2}$
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
0.11115	0.11115	1.2204	1.2204	2.4408	0.0000	0.0000	0.8194	30.000	30.000	4.097
0.0912	0.1311	1.3334	1.1212	2.4546	0.2122	0.0864	0.8148	30.432	29.568	4.074
0.0712	0.1511	1.4609	1.0317	2.4926	0.4352	0.1742	0.8004	30.871	29.129	4.002
0.0512	0.1711	1.6333	0.9498	2.5831	0.6835	0.2646	0.7743	31.323	28.677	3.872
0.0312	0.1911	1.8634	0.8738	2.7372	0.9896	0.3615	0.7307	31.808	28.192	3.654
0.0112	0.2111	2.2835	0.8026	3.0861	1.4809	0.4799	0.6481	32.400	27.600	3.240
0.0001	0.2222	3.7190	0.7648	4.4838	2.9542	0.6580	0.4461	33.294	26.706	2.230

NOTE: The data of columns (9), (10) and (11) are charted in Fig. 1.8, p. 55.

or into the equivalent pair

$$\bar{x} = \frac{U + M}{2} + \frac{U - M}{2} \cdot \frac{K_{p_0'} - K_{p_0''}}{K_{p_0'} + K_{p_0''}} \quad s = \frac{U - M}{2} \cdot \frac{2}{K_{p_0'} + K_{p_0''}} \quad (112)$$

Each pair of values $K_{p_0'}$, $K_{p_0''}$ when substituted into (111) or (112) leads to a combination \bar{x}, s lying on the boundary of the acceptance region; another point on the boundary is given by the combination \bar{x}', s where

$$\bar{x}' = U + M - \bar{x}. \quad (113)$$

Table 1.7 shows the computations for the two-sided acceptance region defined by $p_1 = 0.15$, $p_2 = 0.30$, $\alpha = 0.01$, and $\beta = 0.02$, where defects are represented by values below 25 or above 35. The values $N = 95$ and $k = 0.7645$ are taken from Sec. 4.3. The resulting region is plotted in Fig. 1.8. The figure also shows the acceptance region given by using the pair of one-sided criteria

$$\bar{x} - 0.7645s \geq 25 \quad \bar{x} + 0.7645s \leq 35 \quad (114)$$

It will be observed that the acceptance region for the two-sided test lies entirely within that for the pair of one-sided tests. As \bar{x} approaches U or M , the two boundaries nearly coincide. The difference between the regions is fairly sizable in this case, which involves rather large fractions defective, but for smaller fractions defective the two regions more nearly coincide. For example, keeping $M = 25$ and $U = 35$, but taking $p_1 = 0.001$, $p_2 = 0.0015$, $\alpha = 0.05$, $\beta = 0.10$ (for which Table 1.2 shows $k = 3.0214$) we find that for $\bar{x} = 30$ the maximum acceptable value of s is given by the pair of one-sided tests as 1.655 and by the two-sided test as 1.550; and the difference is less for any other value of \bar{x} . The effect of the difference between a pair of one-sided tests and a two-sided test should be judged by the frequency of lots leading to sample points that would signify acceptance by one test and rejection by the other. One way in which the two-sided test presented here is useful is in judging whether two one-sided tests can be used satisfactorily.

If a two-sided test is used, criteria for reducing or tightening inspection may also be expressed graphically. Upper and lower limits of k_0 should be computed as described in the last paragraph of Sec. 8.2.2 and used as values of k from which to compute two boundary curves according to formulas (111) or (112). If the value of k_0 found in computing the PA lies between the two curves, normal inspection is continued; if it falls below the lower curve, tightened inspection is installed; and if it falls above the upper curve reduced inspection is installed.

11. TECHNICAL NOTES

11.1. Basic Formulas

11.1.1. Assumptions.—Sampling plans for controlling percent defective on the basis of variables involve drawing a sample of N at random

from a lot and computing

$$\bar{x} + ks \quad (115)$$

where

$$\bar{x} = \frac{\Sigma x}{N} \quad (116)$$

$$s^2 = \frac{N \Sigma x^2 - (\Sigma x)^2}{N(N-1)} \quad (117)$$

x represents measurements of the variable being inspected, and k is a constant.

If x is normally distributed, \bar{x} will be normally distributed with mean μ and standard deviation σ/\sqrt{N} , where μ and σ are the lot mean and standard deviation of x . Also, unless N is extremely small, say, less than 5, s will also be nearly normally distributed, its mean and standard deviation being $a\sigma$ and $b\sigma/\sqrt{2(N-1)}$, respectively, where

$$a = \frac{\sqrt{\frac{2}{N-1}} \Gamma\left(\frac{N}{2}\right)}{\Gamma\left(\frac{N-1}{2}\right)} \quad (118)$$

$$b = \sqrt{2(N-1)(1-a)^2} \quad (119)$$

The factors a and b are slightly less than 1 — when $N = 5$, for example, $a = 0.940$ and $b = 0.965$ — and they increase toward 1 as N increases.* They are therefore treated as 1 throughout this chapter; that is, the standard deviation is regarded as normally distributed with mean σ and standard deviation $\sigma/\sqrt{2(N-1)}$.

Since a linear combination of independently distributed variables tends to be normally distributed even when the individual variables depart from normality, $\bar{x} + ks$ will be more nearly normally distributed than s ; in fact, $\bar{x} + ks$ will tend toward normality even if the distribution of x departs from normality. The mean of $\bar{x} + ks$ is $\mu + k\sigma$ and the standard deviation is

$$\sigma \sqrt{\frac{1}{N} + \frac{k^2}{2(N-1)}} \quad (120)$$

* A table of a and b is given in Jennett and Welch, "Control of Proportion Defective," p. 85. This table gives a and b to 3 decimal places for values of N from 5 to 15 by steps of 1, from 15 to 30 by steps of 5, and for 40, 50, 75, and 100. A table of $c_2 = a \sqrt{(N-1)/N}$ to 5 decimal places for values of N from 3 to 25 by steps of 1 and from 25 to 100 by steps of 5 is given by Shewhart, *Economic Control of Quality*, p. 185. Values of $c_2 = a \sqrt{(N-1)/N}$ are given to 4 decimal places for values of N from 2 to 25 by steps of 1 in American Society for Testing Materials Manual, p. 50 of Supplement B; the same table is given in American Standards Association, *Control Chart Method*, p. 39.

11.1.2. Direct Derivation.—The probability that in a sample $\bar{x} + ks$ will be less than U then depends on the difference between U and $\mu + k\sigma$, measured in units of the standard deviation of $\bar{x} + ks$; that is, the probability that $\bar{x} + ks$ will be less than U is the probability that a unit normal deviate will be less than

$$\frac{U - (\mu + k\sigma)}{\sigma \sqrt{\frac{1}{N} + \frac{k^2}{2(N-1)}}} \quad (121)$$

The probability will be ϵ that the test will result in acceptance if

$$\frac{U - (\mu + k\sigma)}{\sigma \sqrt{\frac{1}{N} + \frac{k^2}{2(N-1)}}} = -K_\epsilon = K_{1-\epsilon} \quad (122)$$

where K_ϵ is defined by

$$\frac{1}{\sqrt{2\pi}} \int_{K_\epsilon}^{\infty} e^{-\frac{t^2}{2}} dt = \epsilon \quad (123)$$

We may write (122)

$$\frac{U - \mu}{\sigma} - k = -K_\epsilon \sqrt{\frac{1}{N} + \frac{k^2}{2(N-1)}} \quad (124)$$

$(U - \mu)/\sigma$ is a unit normal deviate that will be exceeded with some probability p , where p is the proportion defective in the lot, so we may write

$$K_p = \frac{U - \mu}{\sigma} \quad (125)$$

Substituting this into (124) and rearranging, we find

$$k = K_p + K_\epsilon \sqrt{\frac{1}{N} + \frac{k^2}{2(N-1)}} \quad (126)$$

If both sides of (126) are decreased by K_p and then squared, a rearrangement of terms gives

$$\left(1 - \frac{K_\epsilon^2}{2(N-1)}\right) k^2 - 2K_p k + \left(K_p^2 - \frac{K_\epsilon^2}{N}\right) = 0 \quad (127)$$

Denoting the coefficient of k^2 by a and the term independent of k by b , k may be expressed in terms of N , K_p , and K_ϵ as

$$k = \frac{K_p + \sqrt{K_p^2 - ab}}{a} \quad (128)$$

If $K_p + k$ is subtracted from both sides of (126) and the equation

multiplied by -1 , we have an equation expressing the fraction defective, in terms of a normal deviate, as a function of N , k , and ϵ ; that is, the abscissa of the OC curve is expressed as a function of the ordinate of the OC curve and of the parameters defining the sampling plan.

Suppose we desire to choose N and k so that the probability will be $1 - \alpha$ of accepting a lot of quality p_1 and β of accepting a lot of quality p_2 , where $\alpha + \beta < 1$ and $p_2 > p_1$. Substituting p_1 and $1 - \alpha$ into (126) gives one equation in N and k , and substituting p_2 and β gives another

$$k = K_1 + K_{1-\alpha} \sqrt{\frac{1}{N} + \frac{k^2}{2(N-1)}} \quad (129)$$

$$k = K_2 + K_\beta \sqrt{\frac{1}{N} + \frac{k^2}{2(N-1)}} \quad (130)$$

where K_1 and K_2 have been written instead of K_{p_1} and K_{p_2} . After subtracting K_1 from (129) and K_2 from (130) and dividing (129) by (130), we have

$$\frac{k - K_1}{k - K_2} = \frac{K_{1-\alpha}}{K_\beta} \quad (131)$$

Solving this for k and replacing $K_{1-\alpha}$ by $-K_\alpha$ gives

$$k = \frac{K_\alpha K_2 + K_\beta K_1}{K_\alpha + K_\beta} \quad (132)$$

N may then be determined by substituting k into (129) or (130) and solving. The solution will be considerably simpler and there will be little if any loss in accuracy if in the denominator of the second term under the radical $N - 1$ is replaced by N . With this approximation (129) becomes

$$k = K_1 + \frac{K_{1-\alpha}}{\sqrt{N}} \sqrt{1 + \frac{k^2}{2}} \quad (133)$$

Subtracting K_1 from both sides, multiplying by $\sqrt{N}/(K_1 - k)$, squaring, and replacing $K_{1-\alpha}$ by $-K_\alpha$ yields

$$N = \frac{K_\alpha^2 \left(1 + \frac{k^2}{2}\right)}{(K_1 - k)^2} \quad (134)$$

Similarly, (130) leads to

$$N = \frac{K_\beta^2 \left(1 + \frac{k^2}{2}\right)}{(k - K_2)^2} \quad (135)$$

By adding (134) and (135) and replacing the k of the denominators by

(132), N may be expressed as in (12); and by substituting for k in the numerators as well as the denominators, N may be expressed directly in terms of K_1 , K_2 , K_a , and K_β , as in (11).

If instead of replacing $N - 1$ by N in (129) and (130) we replace N by $N - 1$, the right-hand sides of (134) and (135) are not affected; but the left-hand sides become $N - 1$. This approximation therefore leads to a value of N one unit larger than that given by (134) and (135). Since N must be an integer, the effects of rounding are of the same order of magnitude as those of replacing $N - 1$ by N . It is because of this approximation that values of N given by (134) and (135) that are not integers should be rounded up instead of to the nearest integer. If the approximation is not made, we find

$$N = \frac{b + \sqrt{b^2 - 16a}}{4a} \quad (136)$$

where

$$a = \left(\frac{K_1 - K_2}{K_a + K_\beta} \right)^2 \quad (137)$$

$$b = k^2 + 2(a + 1) \quad (138)$$

11.1.3. Derivation from General Formulas for Sample Size and Critical Level.—As an alternative derivation of formulas (132) and (134), we may start from the fact that $\bar{x} + ks$ is normally distributed about a certain mean in good lots and about another mean in bad lots and employ the ordinary procedures for testing the mean of a normally distributed variable. Let z represent a normally distributed variable whose mean is Z and whose standard deviation is a function of the sample size of the form

$$\sigma(N) = \sigma \cdot F(N) \quad (139)$$

where $F(N)$ is any function of N that is independent of σ . Suppose a test is required such that the probability is α of rejecting a lot in which the mean is Z_1 and β of accepting a lot in which the mean is Z_2 , where $Z_2 > Z_1$. The test is made by finding z in a sample of N and accepting the lot if $z < A$ or rejecting it if $z > A$, where A is a constant. Then if a lot has a mean of Z_1 , the probability L_1 of acceptance is

$$\begin{aligned} L_1 &= \frac{1}{\sigma(N) \sqrt{2\pi}} \int_{-\infty}^A e^{-\frac{(z-Z_1)^2}{2\sigma^2(N)}} dz \\ &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\frac{A-Z_1}{\sigma(N)}} e^{-\frac{t^2}{2}} dt \end{aligned} \quad (140)$$

where

$$t = \frac{z - Z_1}{\sigma(N)} \quad (141)$$

If the lot mean is Z_2 the probability L_2 of acceptance is

$$\begin{aligned} L_2 &= \frac{1}{\sigma(N) \sqrt{2\pi}} \int_{-\infty}^A e^{-\frac{(z-Z_2)^2}{2\sigma^2(N)}} dz \\ &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\frac{A-Z_2}{\sigma(N)}} e^{-\frac{t^2}{2}} dt \end{aligned} \quad (142)$$

where t is defined by (141) but in terms of Z_2 instead of Z_1 . The appropriate test is then defined by values of A and N such that

$$L_1 = 1 - \alpha \quad (143)$$

$$L_2 = \beta \quad (144)$$

that is,

$$\frac{A - Z_1}{\sigma(N)} = K_\alpha \quad (145)$$

$$\frac{A - Z_2}{\sigma(N)} = -K_\beta \quad (146)$$

On dividing (145) by (146) and solving for A , we find

$$A = \frac{K_\alpha Z_2 + K_\beta Z_1}{K_\alpha + K_\beta} \quad (147)$$

On multiplying both (145) and (146) by $\sigma(N)$, subtracting (146) from (145), replacing $\sigma(N)$ by $\sigma \cdot F(N)$, and solving for $F(N)$, we find

$$F(N) = \frac{Z_2 - Z_1}{\sigma(K_\alpha + K_\beta)} \quad (148)$$

In the ordinary case of testing the mean of a normally distributed variable, $F(N)$ is simply $1/\sqrt{N}$, and this leads to $N = 1/a$, where a is defined by (137).

In applying formulas (147) and (148) to the case of percent defective, we have

$$z = \bar{x} + ks \quad (149)$$

$$Z = \mu + k\sigma \quad (150)$$

$$F(N) = \sqrt{\frac{1}{N} + \frac{k^2}{2(N-1)}} \quad (151)$$

A lot is considered good if

$$\frac{U - \mu}{\sigma} \geq K_1 \quad (152)$$

and bad if

$$\frac{U - \mu}{\sigma} \leq K_2 \quad (153)$$

where $K_1 > K_2$. From (152), using the equality sign, we find

$$\mu = U - K_1\sigma \quad (154)$$

Substituting this into (150) gives

$$\hat{Z}_1 = U + (k - K_1)\sigma \quad (155)$$

Similarly,

$$Z_2 = U + (k - K_2)\sigma \quad (156)$$

Substituting from (151), (155), and (156) into (148), we have

$$\sqrt{\frac{1}{N} + \frac{k^2}{2(N-1)}} = \frac{K_1 - K_2}{K_\alpha + K_\beta} \quad (157)$$

for which (136) is the solution. Substituting from (155) and (156) into (147) gives

$$A = \frac{K_\alpha[U + (k - K_2)\sigma] + K_\beta[U + (k - K_1)\sigma]}{K_\alpha + K_\beta} \quad (158)$$

$$= \frac{K_\alpha(U + k\sigma) + K_\beta(U + k\sigma)}{K_\alpha + K_\beta} - \frac{K_\alpha K_2 + K_\beta K_1}{K_\alpha + K_\beta} \sigma$$

$$A = U + k\sigma - \frac{K_\alpha K_2 + K_\beta K_1}{K_\alpha + K_\beta} \sigma \quad (159)$$

Any combination of values of k and A that satisfy this equation will be satisfactory values for the multiple of the standard deviation and the rejection level of $\bar{x} + ks$, but most pairs will be unusable because calculation of the rejection level A from (159) will require knowledge of σ . If, however, we set

$$k = \frac{K_\alpha K_2 + K_\beta K_1}{K_\alpha + K_\beta} \quad (160)$$

this problem is solved by the disappearance of σ , and the rejection level becomes simply

$$A = U \quad (161)$$

The value of k from (160) may then be substituted into (157) to determine N . If we replace $N - 1$ by N , the value of N given by (157) is the same as that given by formulas (134) and (135), otherwise it is the same as that given by (136).

11.1.4. Two-sided Criterion.—The basis for the two-sided test presented in Sec. 10.2.3 is the fact that, because $\bar{x} + ks$ can be assumed symmetrically distributed about $\mu + k\sigma$, the boundary between acceptable and unacceptable combinations of \bar{x} and s corresponds with the boundary between combinations of μ and σ for which a lot has more or less than a 50 percent chance of acceptance. Thus, in Fig. 1.8 if the \bar{x} and s axes are interpreted as μ and σ axes, any lot represented by a point on the boundary line has an equal chance of acceptance or rejection, that is, corresponds with the indifference percent defective. For the two-sided test it is clear that the indifference quality is the same as for a one-sided test; for when σ is very small and μ is near U or M , the two-

sided and one-sided tests become virtually equivalent. Thus, the procedure for finding the boundary of the two-sided acceptance region begins by finding the proper indifference quality p_0 . For any value of μ , a value of σ is found such that the fraction p'_0 below M plus the fraction p''_0 above U is equal to p_0 ; these values of μ and σ are then taken as the coordinates of a point \bar{x}, s on the acceptance boundary. For computational purposes, starting with μ and finding the proper σ is cumbersome, but the parametric equations (111) and (112), which start with an arbitrary division of p_0 into two parts p'_0 and p''_0 , are easily used. Given p'_0 and p''_0 , we have

$$\mu - K_{p'_0}\sigma = M \quad (162)$$

and

$$\mu + K_{p''_0}\sigma = U \quad (163)$$

Equations (111) and (112) represent solutions of (162) and (163) for μ and σ in terms of U , M , $K_{p'_0}$, and $K_{p''_0}$, and thus give the coordinates of a point \bar{x}, s on the acceptance boundary.

11.2. Approximations in the Basic Formulas

Four incorrect assumptions are made in deriving the preceding formulas:

(1) That $\bar{x} + ks$ is normally distributed; actually, it is not quite normally distributed, since s is not.

(2) That s is distributed about a mean of σ ; actually, it is distributed about a mean of $a\sigma$, where $a < 1$ and is defined by equation (118).

(3) That s is distributed with standard deviation $\sigma/\sqrt{2(N-1)}$; actually, it is distributed with standard deviation of $b\sigma/\sqrt{2(N-1)}$, where $b < 1$ and is defined by equation (119).

(4) That s is distributed with standard deviation $\sigma/\sqrt{2N}$. This assumption applies only to formulas (134) and (135) for N .

All these assumptions can be avoided by utilizing the non-central t distribution, tables of which have been published by Johnson and Welch. In fact, the values of N and k and the corresponding true values of p_1 and p_2 given in Table 1.2 were computed with the aid of tables of the non-central t distribution. The effect of the approximations in the formulas can therefore be examined by comparing the values they give with those given in Table 1.2. Such a comparison exaggerates somewhat the inaccuracy of the formulas because in preparing the table some effort was expended, as is explained in Sec. 11.5, to make the best adjustment to the discontinuous nature of N , rather than entering the first values of N and k found. Similar adjustments could be made in using the formulas. Section 4.7 includes a comparison between the results given by the formulas and those in Table 1.2, the comparison being made for the smallest sample size, namely, 6, included in Table 1.2. (It will be noted

that all four of the incorrect assumptions underlying the formulas rapidly become very nearly correct as N increases.)

TABLE 1.8

COMPARISON OF APPROXIMATE AND EXACT VALUES OF N AND k

The exact values of k in column (2) have been computed from the non-central t distribution, taking $p_1 = 0.05$, $\alpha = 0.01$, and N as shown in column (1). The exact values of p_2 for which $\beta = 0.10$ have then been computed and entered in column (3). From these p_2 , taking $\beta = 0.10$, $p_1 = 0.05$, and $\alpha = 0.01$, approximate values of N and k have been computed from formulas (10) and (11) or (12). The true values of p_1 and p_2 for which $\alpha = 0.01$ and $\beta = 0.10$ have been computed from the non-central t distribution.

Exact			Approximate			
N	k	p_2	N	k	true p_1	true p_2
(1)	(2)	(3)	(4)	(5)	(6)	(7)
5	0.5445	0.5428	5	0.5150	0.0541	0.5519
10	0.8037	0.3774	10	0.7856	0.0524	0.3830
15	0.9292	0.3033	15	0.9163	0.0517	0.3071
20	1.0083	0.2604	20	0.9983	0.0513	0.2633
25	1.0643	0.2332	25	1.0560	0.0510	0.2344
30	1.1069	0.2119	30	1.1000	0.0509	0.2137
35	1.1409	0.1966	35	1.1348	0.0507	0.1981
40	1.1688	0.1846	40	1.1633	0.0507	0.1859
45	1.1922	0.1748	45	1.1874	0.0506	0.1759
50	1.2125	0.1666	50	1.2082	0.0505	0.1676
65	1.2592	0.1489	64	1.2556	0.0501	0.1500
75	1.2828	0.1404	74	1.2797	0.0501	0.1413
100	1.3264	0.1256	99	1.3241	0.0501	0.1262

Table 1.8 shows a few comparisons of the values of k and N given by formulas (132) and (134) or (135) with the exact values. In these cases α has been fixed at 0.01 and p_1 at 0.05. Various values of N have been selected and the resulting lot quality p_2 for which $\beta = 0.10$ has been calculated from the non-central t distribution. Thus the exact values of N and k result in an OC curve passing exactly through the points defined by p_1, α and p_2, β . If p_1, α and p_2, β are both selected arbitrarily, it is not usually possible to find values of N and k such that the OC curve passes exactly through both points. Thus the exact values of N and k given in Table 1.8 are more exact than could ordinarily be achieved in practical problems, while those given by the formulas are characteristic of the accuracy realizable in practice. Columns (6) and (7) of the table show the true values of p_1 and p_2 for which $\alpha = 0.01$ and $\beta = 0.10$ when the approximate N and k are used. The differences between 0.05 and the values in column (6) and between the values in columns (3) and (7)

are a measure of the effect of the approximations. An alternative measure would be the error in the true α and β at the intended p_1 and p_2 ; this error would probably be smaller than that in p_1 and p_2 because the OC curves are usually fairly flat in the neighborhood of p_1 and p_2 . While it cannot be claimed that Table 1.8 gives a representative coverage of all kinds of plans, it can be claimed that, for those comparisons given, the discrepancy between the approximate and exact results is maximized.

11.3. Computational Formulas

The use of the acceptance criterion

$$\bar{x} + ks \leq U \quad (164)$$

requires the calculation of the sample mean \bar{x} and the standard deviation s . The acceptance criterion can, however, be expressed in terms of simpler functions of the observations, namely,

$$X = \Sigma x \quad (\text{sum of the observations}) \quad (165)$$

$$Y = \Sigma x^2 \quad (\text{sum of the squares of the observations}) \quad (166)$$

If k is positive, as it almost invariably will be, the lot may be rejected without regard to Y if

$$X > NU \quad (167)$$

In this case, \bar{x} exceeds U , so since s cannot be negative, $\bar{x} + ks$ exceeds U .

The values of \bar{x} and s for a sample of N observations can be calculated from

$$\bar{x} = \frac{\Sigma x}{N} \quad (168)$$

and

$$s = \sqrt{\frac{N \Sigma x^2 - (\Sigma x)^2}{N(N-1)}} \quad (169)$$

In terms of X and Y , equations (168) and (169) can be written

$$\bar{x} = \frac{X}{N} \quad (170)$$

and

$$s = \sqrt{\frac{NY - X^2}{N(N-1)}} \quad (171)$$

Replacing \bar{x} and s in (164) by their values from (170) and (171) gives

$$\frac{X}{N} + k \sqrt{\frac{NY - X^2}{N(N-1)}} \leq U \quad (172)$$

Subtracting X/N from both sides of inequality (172) and squaring gives

$$\frac{NY^2 - X^2}{N(N-1)} \cdot k^2 \leq U^2 - \frac{2XU}{N} + \frac{X^2}{N^2} \quad (173)$$

Clearing fractions and rearranging terms gives

$$Y \leq aX^2 - bX + c \quad (174)$$

where

$$a = \frac{Nk^2 + N - 1}{N^2k^2} \quad (175)$$

$$b = \frac{2U(N - 1)}{Nk^2} \quad (176)$$

$$c = \frac{U^2(N - 1)}{k^2} \quad (177)$$

If inequality (174) is fulfilled, the lot is accepted; if inequality (174) is not fulfilled, the lot is rejected.

Using the equality sign in (174) gives the equation of a parabola

$$Y_R = aX^2 - bX + c \quad (178)$$

which shows, for each value of X , the maximum value of Y permitting acceptance, that is, the upper boundary of the acceptance region or the lower boundary of the rejection region.

The minimum value of the curve Y_R gives a value of Y below which the lot is acceptable without regard to X . Differentiating (178) with respect to X gives

$$\frac{dY_R}{dX} = 2aX - b \quad (179)$$

Setting $\frac{dY_R}{dX}$ equal to zero and solving for X gives

$$\check{X} = \frac{b}{2a} \quad (180)$$

Since

$$\frac{d^2Y_R}{dX^2} = 2a > 0 \quad (181)$$

\check{X} is the value of X at which the minimum value \check{Y}_R of Y_R occurs. Replacing X in (178) by the value of \check{X} given by (180) gives, after simplification,

$$\check{Y}_R = c - \frac{b^2}{4a} \quad (182)$$

Substituting the values of a , b , and c given by (175), (176), and (177) into (180) and (182), and simplifying, gives

$$\check{X} = \frac{UN(N - 1)}{Nk^2 + N - 1} \quad (183)$$

$$\check{Y}_R = \frac{U^2N(N - 1)}{Nk^2 + N - 1} \quad (184)$$

The coordinates of the minimum point, $X = \check{X}$ and $Y = \check{Y}_R$, can be

approximated by replacing by N the $N - 1$ in the denominators of (183) and (184)

$$\text{Approximate } \check{X} = \frac{U(N-1)}{k^2 + 1} \quad (185)$$

$$\text{Approximate } \check{Y}_R = \frac{U^2(N-1)}{k^2 + 1} \quad (186)$$

These approximate values are smaller than the exact values since they were obtained by increasing the denominators; if, therefore,

$$Y \leq \frac{U^2(N-1)}{k^2 + 1} \quad (187)$$

Y will certainly be less than the minimum value of Y_R , and the lot may be accepted without regard to X .

The acceptance region has a lower boundary corresponding, for each value of X , with the minimum value of Y algebraically possible. The sum of the squares of the deviations of the observations from their mean can be written

$$\Sigma(x - \bar{x})^2 = \Sigma x^2 - \frac{(\Sigma x)^2}{N} \quad (188)$$

or, in terms of X and Y

$$\Sigma(x - \bar{x})^2 = Y - \frac{X^2}{N} \quad (189)$$

Since $\Sigma(x - \bar{x})^2$ cannot be negative,

$$Y \geq \frac{X^2}{N} \quad (190)$$

For any given sum of observations X , the value of Y will be $\frac{X^2}{N}$ when the sum of the squares of the deviations of the observations from their mean is zero; that is, when all the observations are equal. The lower boundary of the acceptance region, or upper boundary of the error region, is, therefore,

$$Y_R = \frac{X^2}{N} \quad (191)$$

A sample point lying below this line would indicate a computational error.

By equating \check{Y}_R and Y_R given by (178) and (191), it can be shown that the lower and upper boundaries of the acceptance region meet at the point $X = NU$ and $Y = NU^2$. The two curves are tangent at this point. Beyond it, they again enclose an area similar to the acceptance region; this area beyond the point of tangency would be the acceptance region for a test in which k is negative.

The graphical procedure of Sec. 7.3.1 consists of drawing on a chart the upper and lower boundaries of the acceptance region, given by (178) and (191); a point representing the sample is plotted on this chart and the lot accepted or rejected according as the point lies within or above the acceptance region. This graphical procedure is impractical, however, when the observations are large. In this case, the range of variation in Y as X varies is large relative to the width of the acceptance region; and the upper and lower boundaries of the acceptance region are too close for most practical purposes.

An adjustment of the observations can be made (a) to overcome this difficulty in the graphical procedure or (b) to find a criterion more effective than formula (187) in permitting immediate acceptance. The adjustment consists of subtracting an adjustment constant A from each of the observations, A being chosen according to the purpose (a) or (b) for which the adjustment is being used. It is not necessary to adjust each observation; it is necessary only to compute the sum of the squares of the adjusted observations Y' from X and Y by

$$\begin{aligned} Y' &= \Sigma(X - A)^2 \\ &= Y - 2AX + NA^2 \end{aligned} \quad (192)$$

Adjusting Y_u and Y_L , given in (178) and (191), by (192) (that is, subtracting $2AX$ and adding NA^2) gives the upper and lower boundaries of the acceptance region

$$Y'_u = aX^2 - (b + 2A)X + (c + NA^2) \quad (193)$$

$$Y'_L = \frac{X^2}{N} - 2AX + NA^2 \quad (194)$$

where a , b , and c are defined by (175), (176), and (177).

It can be shown that the minimum value \check{Y}'_r of Y'_r is

$$\check{Y}'_r = \frac{(U - A)^2 N(N - 1)}{Nk^2 + N - 1} \quad (195)$$

Replacing by N the $N - 1$ in the denominator of \check{Y}'_r gives the simplified criterion for immediate acceptance

$$Y' \leq \frac{(U - A)^2(N - 1)}{k^2 + 1} \quad (196)$$

If the graphical procedure is used, the adjustment constant A should be chosen so as to minimize the variation in Y as X varies over the region of likely sample values. This flattens the curves defining the acceptance region, thus enabling the acceptance region to encompass a larger portion of the chart's area and thereby improving the accuracy of

plotting. To determine the optimum value of A , consider the slope of Y'_R at a given value of X

$$\frac{dY'_R}{dX} = \frac{2X}{N_0} - 2A \quad (197)$$

For a given value of X , the slope is zero when $A = X/N$. The optimum value of A depends, therefore, on the observed value of X . If before the sample is inspected μ' is the best estimate of the mean of the characteristic being inspected, the optimum value of A , for graphical purposes, is

$$A = \mu' \quad (198)$$

since the expected value of X is $N\mu'$.

If the graphical procedure is not used, the adjustment constant A should be chosen so as to maximize the effectiveness of formula (196) in permitting immediate acceptance. This involves finding the value of A that minimizes the Y corresponding to the minimum value $Y' = \check{Y}'_R$. Differentiating (193) with respect to X gives

$$\frac{dY'_R}{dX} = 2aX - (b + 2A) \quad (199)$$

Since

$$\frac{d^2Y'_R}{dX^2} = 2a > 0 \quad (200)$$

setting $\frac{dY'_R}{dX}$ equal to zero and solving for X gives the value of X at which Y'_R is a minimum, namely,

$$X = \frac{b + 2A}{2a} \quad (201)$$

The value of Y'_R calculated from (193) for the point whose abscissa is given by (201) is the minimum value of Y'_R

$$\check{Y}'_R = -\frac{(b + 2A)^2}{4a} + (c + NA^2) \quad (202)$$

The value of \check{Y}'_R given by (195) can be obtained from (202) by replacing a , b , and c by their values given by (175), (176), and (177). Finding the value of Y corresponding to $Y' = \check{Y}'_R$, that is, adding $2AX$ to, and subtracting NA^2 from, (202) gives

$$\begin{aligned} Y &= -\frac{(b + 2A)^2}{4a} + (c + NA^2) + 2AX - NA^2 \\ &= -\frac{(b + 2A)^2}{4a} + c + 2AX \end{aligned} \quad (203)$$

Now, the optimum value of A is that value which makes the Y corresponding to the minimum value \check{Y}'_R as large as possible, since, for a given

value of X , if Y is less than the value given by (203), the lot is accepted. Differentiating (203) with respect to A gives

$$\frac{dY}{dA} = -\frac{(b + 2A)}{a} + 2X \quad (204)$$

Since

$$\frac{d^2Y}{dA^2} = -\frac{2}{a} < 0 \quad (205)$$

setting $\frac{dY}{dA}$ equal to zero and solving for A gives the value of A at which Y is a maximum, namely,

$$A = aX - \frac{b}{2} \quad (206)$$

The value of A given in (206) is a function of X , so the optimum value of A depends on the observed value of X . If before the sample is inspected μ' is the best estimate of \bar{x} , the anticipated value of X is $N\mu'$. Replacing X in (206) by its anticipated value gives

$$A = aN\mu' - \frac{b}{2} \quad (207)$$

Replacing a and b in (207) by their values given by (175) and (176), and simplifying, gives

$$A = \frac{(Nk^2 + N - 1)\mu' - (N - 1)U}{Nk^2} \quad (208)$$

Replacing by N the $N - 1$ in the numerator of (208) gives

$$\text{Approximate } A = \frac{(k^2 + 1)\mu' - U}{k^2} \quad (209)$$

Using the value of A given by either (208) or (209) makes (196) very nearly the most effective in permitting immediate acceptance. In terms of Y , replacing the A in (203) by (207), and simplifying, gives the linear condition for acceptance

$$Y \leq c' - b'X \quad (210)$$

where

$$b' = b - 2N\mu'a \quad (211)$$

$$c' = c - N^2\mu'^2a \quad (212)$$

and a , b , and c are defined by (175), (176), and (177).

11.4. Use of Non-central t Distribution

11.4.1. Introduction.—The acceptance criterion

$$\bar{x} + ks \leq U \quad (213)$$

can be written

$$\frac{U - \bar{x}}{s} \geq k \quad (214)$$

The quantity $(U - \bar{x})/s$ is a function of the sample data and k is a constant; using the acceptance criterion (214) is thus equivalent to comparing the value of the sample statistic $(U - \bar{x})/s$ with a minimum level for acceptance k .

If many samples of N observations are chosen at random from the same population (or lot), the values of $(U - \bar{x})/s$ obtained from the various samples will vary. The proper determination of k requires a knowledge of the sampling distribution of $(U - \bar{x})/s$.

The distribution of the quantity t , defined as

$$t = \sqrt{N} \left(\frac{U - \bar{x}}{s} \right) \quad (215)$$

is known as the non-central t distribution, of which the familiar Student's t distribution is a special case corresponding with $Ex = U$. Tables of the non-central t distribution with an explanation of their application to the problems considered in this chapter have been given by Johnson and Welch.

11.4.2. Notation Used in the Tables.—It will be necessary to use the notation of Johnson and Welch to explain the application of their tables to the problems discussed in this chapter. The following list indicates the changes in notation:*

	This chapter	Johnson and Welch
Value of variable that defines quality.....	U	L
Sample statistic.....	$k_o = \frac{U - \bar{x}}{s}$	$u = \frac{L - \bar{x}}{s}$
Acceptable level of statistic.....	k	u_0
Normal deviate corresponding with proportion p defective in lot.....	K_p	U
Normal deviate corresponding with probability e of accepting a lot.....	K_e	K

* A word of explanation is in order about our departure from the Johnson-Welch and Jennett-Welch notation, since their notation is satisfactory and established. Throughout all three of our volumes the letter L is consistently used to represent the ordinate of an OC curve; as a substitute U has the mnemonic advantage of association with "upper limit." It seems unnecessary to use two symbols for the normal deviate, since the type of subscript (Greek letter, numeral, and so forth) can discriminate between normal deviates defining quality and those describing operating characteristics. For the sample statistic, k accords with the lot parameter K . Logic suggests a subscript for the acceptable level of the statistic, and Johnson and Welch use 0; but because the acceptable level enters the analysis so frequently and other values so seldom, we use no subscript. Logic also suggests a subscript for a particular observed value of the statistic, and we use o .

In the notation of Johnson and Welch, the acceptance criterion (214) becomes

$$u \geq u_a \quad (216)$$

Let z be a quantity distributed normally about zero with unit standard deviation, and let w be a quantity distributed independently of z and in the same way as an estimate of variance computed from a sample from a normal population containing f degrees of freedom. That is, w is distributed as χ^2/f with f degrees of freedom. If t is defined by

$$t = \frac{z + \delta}{\sqrt{w}} \quad (217)$$

where δ is some constant, then t has the non-central t distribution, depending only on the eccentricity δ and the number of degrees of freedom f .

To see that the statistic u is closely related to the non-central t distribution, consider the distribution of values of u from random samples of N observations from a normal population with mean μ and standard deviation σ . Suppose that exactly a proportion p of the items in the population exceed a given limit L and that U is the standardized normal deviate exceeded with probability p , that is,

$$\frac{1}{\sqrt{2\pi}} \int_U^\infty e^{-\frac{r^2}{2}} dr = p \quad (218)$$

Let \bar{x} and s be the sample mean and standard deviation, respectively. Then, in the notation of Johnson and Welch, $\sqrt{N} u$ can be written as (217) with

$$z = \frac{\sqrt{N}(\bar{x} - \mu)}{\sigma} \quad (219)$$

$$w = \frac{s^2}{\sigma^2} \quad (220)$$

$$f = N - 1 \quad (221)$$

$$\delta = \sqrt{N} U \quad (222)$$

Hence, $\sqrt{N} u$ is distributed as a non-central t with $f = N - 1$ and $\delta = \sqrt{N} U$.

The distribution of non-central t requires a triple-entry table, since the probability that t exceeds a given level t_0 depends on f , δ , and t_0 . This probability is denoted by $P(f, \delta, t_0)$. Johnson and Welch also use $t(f, \delta, \epsilon)$ to denote that value of t_0 for which the probability $P(f, \delta, t_0)$ takes a specified value ϵ . The value of δ that makes $P(f, \delta, t_0) = \epsilon$ is denoted by $\delta(f, t_0, \epsilon)$.

11.4.3. Description of the Tables.—The problems for which the non-central t tables are used in this chapter require the evaluation of either

$\delta(f, t_0, \epsilon)$ or $t(f, \delta, \epsilon)$. Table IV given by Johnson and Welch facilitates the direct calculation of these for 17 probability levels corresponding with ϵ and $1 - \epsilon$ equal to 0.005, 0.01, and 0.025, 0.05, 0.1, 0.2, 0.3, 0.4, and 0.5.

In Table IV, a quantity $\lambda = \lambda(f, t_0, \epsilon)$ is given such that

$$\delta(f, t_0, \epsilon) = t_0 - \lambda \sqrt{1 + \frac{t_0^2}{2f}} \quad (223)$$

and

$$t(f, \delta, \epsilon) = \frac{\delta + \lambda \sqrt{1 + \frac{\delta^2}{2f} - \frac{\lambda^2}{2f}}}{1 - \frac{\lambda^2}{2f}} \quad (224)$$

Equations (42) and (21) of this chapter are essentially approximations for equations (223) and (224), respectively, with λ in (223) and (224) replaced by K_ϵ , the normal deviate exceeded with probability ϵ . Even for small samples, it is found that λ does not differ much from K_ϵ .

Table IV consists of nine double-entry panels (one for each of the values of ϵ listed above) showing λ as a function of f and t_0 . Values of λ are given corresponding to $f = 4, 5, 6, 7, 8, 9, 16, 36, 144$, and ∞ . In order to simplify interpolation for intermediate values of f greater than 9, the values of $f = 9, 16, 36, 144$ and ∞ are such that $12/\sqrt{f} = 4, 3, 2, 1$, and 0, respectively; that is, λ is tabled at equal intervals of $12/\sqrt{f}$. The whole range of t_0 from $-\infty$ to ∞ is covered as follows: For $t_0/\sqrt{2f}$ between $-\infty$ and -0.75 or between $+0.75$ and $+\infty$, λ is tabled against the quantity

$$y = \frac{1}{\sqrt{1 + \frac{t_0^2}{2f}}} \quad (225)$$

For $t_0/\sqrt{2f}$ between -0.75 and $+0.75$, λ is tabled against

$$y' = \frac{\frac{t_0}{\sqrt{2f}}}{\sqrt{1 + \frac{t_0^2}{2f}}} \quad (226)$$

11.4.4. Calculation of $\delta(f, t_0, \epsilon)$.—For given f , t_0 , and $\epsilon \leq 0.5$, the steps required for the calculation of $\delta(f, t_0, \epsilon)$ are given below. For $\epsilon > 0.5$, the relation

$$\delta(f, t_0, \epsilon) = -\delta(f, -t_0, 1 - \epsilon) \quad (227)$$

is used. That is, if $\delta(9, 12, 0.95)$ is required, calculate $\delta(9, -12, 0.05)$ by the procedure outlined below and take the negative of this value as the required value of $\delta(9, 12, 0.95)$.

Step 1. Calculate $t_0/\sqrt{2f}$.

Step 2. Find $y = \frac{1}{\sqrt{1 + t_0^2/2f}}$ or $y' = \frac{t_0/\sqrt{2f}}{\sqrt{1 + t_0^2/2f}}$ according as $\left| \frac{t_0}{\sqrt{2f}} \right|$ is greater than or less than 0.75.

Step 3. If f is greater than 9, calculate $12/\sqrt{f}$.

Step 4. From the panel of Table IV corresponding with the given ϵ , obtain $\lambda = \lambda(f, t_0, \epsilon)$ by interpolating with respect to the quantities obtained in steps 2 and 3.

Step 5. Calculate $\delta(f, t_0, \epsilon) = t_0 - \lambda \sqrt{1 + t_0^2/2f}$.

11.4.5. Calculation of $t(f, \delta, \epsilon)$.—The calculation of $t(f, \delta, \epsilon)$ is accomplished by an iterative method, since λ is given in Table IV as a function of t_0 . The successive steps in the iterative method for calculating $t(f, \delta, \epsilon)$ for given f , δ , and $\epsilon \leq 0.5$ are given below. For $\epsilon > 0.5$, the relation

$$t(f, \delta, \epsilon) = -t(f, -\delta, 1 - \epsilon) \quad (228)$$

is used. That is, if $t(9, 5, 0.90)$ is required, calculate $t(9, -5, 0.10)$ by the procedure outlined below, and take the negative of this value as the required $t(9, 5, 0.90)$.

Step 1. Determine K_ϵ , the normal deviate exceeded with probability ϵ , which can be found in Table 1.1.

Step 2. Calculate the first approximation t_1 from

$$t_1 = \frac{\delta + K_\epsilon \sqrt{1 + \frac{\delta^2}{2f} - \frac{K_\epsilon^2}{2f}}}{1 - \frac{K_\epsilon^2}{2f}}$$

Step 3. Calculate $t_1/\sqrt{2f}$.

Step 4. Find $y = \frac{1}{\sqrt{1 + t_1^2/2f}}$ or $y' = \frac{t_1/\sqrt{2f}}{\sqrt{1 + t_1^2/2f}}$ according as $\left| \frac{t_1}{\sqrt{2f}} \right|$ is greater than or less than 0.75.

Step 5. If f is greater than 9, calculate $12/\sqrt{f}$.

Step 6. From the panel of Table IV corresponding with the given ϵ , obtain $\lambda_1 = \lambda(f, t_1, \epsilon)$ by interpolating with respect to the quantities obtained in steps 4 and 5.

Step 7. Calculate a second approximation t_2 from

$$t_2 = \frac{\delta + \lambda_1 \sqrt{1 + \frac{\delta^2}{2f} - \frac{\lambda_1^2}{2f}}}{\left(1 - \frac{\lambda_1^2}{2f}\right)}$$

Step 8. Repeat steps 3 through 7, replacing t_1 by t_2 , and calculate a third approximation t_3 . Repeat these steps until two successive approximations are the same; usually not more than two approximations are required. Take for $t(f, \delta, \epsilon)$ the value so obtained.

11.4.6. Illustration of the Use of the Non-central t Tables in Specific Problems

Problem I. Given: N, p_1, ϵ (in our notation, $N, p_1, 1 - \alpha$ or N, p_2, β)

Required: u_0 (in our notation, k)

A single-sampling plan based on variables is defined by a sample size N and a value u_0 of the statistic u . If N is fixed, u_0 can be determined so that the operating-characteristic curve for the plan passes through a specified point (p_1, ϵ) ; that is, for a fixed sample size, a plan is chosen for which the probability of accepting lots of quality p_1 is ϵ .

For given N, p_1 , and ϵ , the value u_0 that defines the plan is given, in the notation of Johnson and Welch, by

$$\sqrt{N}u_0 = t(N - 1, \sqrt{N}U_1, \epsilon) \quad (229)$$

where U_1 is the normal deviate exceeded with probability p_1 . Thus, for a given sample size N , quality (fraction defective) p_1 , and probability of acceptance ϵ , the determination of u_0 requires the calculation of $t(f, \delta, \epsilon)$ where $f = N - 1$ and $\delta = \sqrt{N}U_1$.

An outline of the method for determining u_0 for given values of N, p_1 and ϵ is given below.

Given: N = sample size

p_1 = a proportion defining quality

ϵ = desired probability of accepting lots of quality p_1

Step 1. Determine U_1 , the normal deviate exceeded with probability p_1 , from Table 1.1.

Step 2. Calculate

$$\begin{aligned} f &= N - 1 \\ \delta &= \sqrt{N}U_1 \end{aligned}$$

Step 3. Calculate $t(f, \delta, \epsilon)$ by the method described in Sec. 11.4.5.

Step 4. Calculate $u_0 = t(f, \delta, \epsilon) / \sqrt{N}$.

Problem II. Given: N, u_0, ϵ (in our notation, N, k, L_p)

Required: p

For every single-sampling plan (defined by N and u_0), there is an operating-characteristic (OC) curve which shows the probability ϵ of

accepting a lot of quality p . From the Johnson and Welch tables we can compute the values of p corresponding to ϵ or $1 - \epsilon$ equal to 0.005, 0.01, 0.025, 0.05, 0.1, 0.2, 0.3, 0.4, or 0.5. This requires finding $\delta(f, t_0, \epsilon)$ where $f = N - 1$ and $t_0 = \sqrt{N}u_0$. The value of U corresponding to this value of δ is δ/\sqrt{N} . The value of p corresponding to the given ϵ is then the probability that a normal deviate will exceed this U , which may be found from Table 1.5.

Step 1. Calculate

$$\begin{aligned} t_0 &= \sqrt{N}u_0 \\ f &= N - 1 \end{aligned}$$

Step 2. Calculate $\delta(f, t_0, \epsilon)$ by the method described in Sec. 11.4.4.

Step 3. Calculate $U = \delta(f, t_0, \epsilon)/\sqrt{N}$.

Step 4. Obtain the required p by entering Table 1.5 with K equal to the value of U found in step 3.

11.4.7. Work Sheets.—Suppose that the sample size is fixed at 30, and a plan is required for which a lot having 0.1 percent defective will be accepted with probability 0.99. That is, $N = 30$, $p_1 = 0.001$, and $\epsilon = 0.99$. Work sheets 1, 2, and 3 (Tables 1.9, 1.10, and 1.11) represent the calculations necessary to determine u_0 ; work sheet 4 (Table 1.12) represents those for the OC curve. The numerical entries have been rounded from calculations originally carried to more decimal places, so they do not always agree exactly with operations carried out on the 5-decimal-place figures shown.

TABLE 1.9
WORK SHEET 1 FOR DETERMINING u_0 (IN OUR NOTATION k) FROM NON-CENTRAL t TABLES

Row number	Operation	Result	Example
(1)	(2)	(3)	(4)
(1)	Given	p_1	0.001
(2)	Given	ϵ	0.99
(3)	Given	N	30.
(4)	Table 1.1	U_1	3.09023
(5)	$\sqrt{(3)}$	\sqrt{N}	5.47723
(6)	(3) - 1	$f = N - 1$	29.
(7)	(4) \times (5)	$\delta = \sqrt{N} U_1$	16.92590
(8)	Sheet 2, row (14), last column	$t(f, \delta, \epsilon)$	12.47223
(9)	(8) \div (5)	$u_0 = \frac{t(f, \delta, \epsilon)}{\sqrt{N}}$	2.27711

TABLE 1.10
WORK SHEET 2 FOR DETERMINING u_0 —COMPUTATION OF $t(f, \delta, \epsilon)$

Row number (1)	Operation (2)	Result (3)	First approximation (4)	Second approximation (5)
(1)	Sheet 1, line 6	f	29	←
(2)	Sheet 1, line 7*	δ or $-\delta$	-16.92590	←
(3)	Sheet 1, line 2*	ϵ or $1 - \epsilon$	0.01	←
(4)	$2 \times (1)$	$2f$	58	←
(5)	$(2)^2$	δ^2	286.48606	←
(6)	$(5) \div (4)$	$\frac{\delta^2}{2f}$	4.93941	←
(7)	Table 1.1	K_ϵ	2.32635	2.321†
(8)	$(7)^2$	K_ϵ^2	5.41190	5.38704
(9)	$(8) \div (4)$	$\frac{K_\epsilon^2}{2f}$	0.09331	0.09288
(10)	$1 + (6) - (9)$	$1 + \frac{\delta^2}{2f} - \frac{K_\epsilon^2}{2f}$	5.84611	5.84654
(11)	$\sqrt{(10)}$	$\sqrt{1 + \frac{\delta^2}{2f} - \frac{K_\epsilon^2}{2f}}$	2.41787	2.41796
(12)	$(2) + (7) \times (11)$	$\delta + K_\epsilon \sqrt{1 + \frac{\delta^2}{2f} - \frac{K_\epsilon^2}{2f}}$	-11.30109	-11.31381
(13)	$1 - (9)$	$1 - \frac{K_\epsilon^2}{2f}$	0.90669	0.90712
(14)	$(12) \div (13)$	$t = t(f, \delta, \epsilon)$	-12.46410	-12.47223
(15)	$\sqrt{(4)}$	$\sqrt{2f}$	7.61577	←
(16)	$(14) \div (15)$	$\frac{t}{\sqrt{2f}}$	-1.63662	-1.63768
(17)	$(14)^2$	t^2	155.35379	155.56660
(18)	$(17) \div (4)$	$\frac{t^2}{2f}$	2.67851	2.68201
(19)	$1 + (18)$	$1 + \frac{t^2}{2f}$	3.67851	3.68201
(20)	$\sqrt{(19)}$	$\sqrt{1 + \frac{t^2}{2f}}$	1.91795	1.91886
(21)	$1 \div (20)$	$y = 1 / \sqrt{1 + \frac{t^2}{2f}}$	0.52139	0.52114
(22)	$(16) \div (20)$	$y' = \frac{t}{\sqrt{2f}} / \sqrt{1 + \frac{t^2}{2f}}$	‡	‡
(23)	$\sqrt{(1)}$	\sqrt{f}	5.38516	←
(24)	$12 \div (23)$	$\frac{12}{\sqrt{f}}$	2.22834	←
(25)	Sheet 3, row (17), last column	λ	2.321	2.321

* Since $\epsilon > 0.5$, we change the sign of δ and replace ϵ by $1 - \epsilon$.

† The figure in row (7), column (5) is the value of λ_1 given in row (25), column (4) and is used in place of K_ϵ in the succeeding calculations for λ_2 .

‡ No figures are given for y' in this example because $t_0/\sqrt{2f} > 0.75$.

TABLE 1.11
WORK SHEET 3 FOR DETERMINING u_0 —LINEAR INTERPOLATION FOR $\lambda(a,b)$

Row number	Operation	Result	First approximation	Second approximation
(1)	(2) -	(3)	(4)	(5)
(1)	Sheet 2, line 21*	a	0.52139	0.52114
(2)	Sheet 2, line 24*	b	2.2283	2.2283
(3)	Table IV*	a_1	0.5	0.5
(4)	Table IV*	a_2	0.6	0.6
(5)	Table IV*	b_1	3.	3.
(6)	Table IV*	b_2	2.	2.
(7)	(3) - (1)	$c_1 = \frac{a_1 - a}{a_1 - a_2}$	0.2139	0.2114
(8)	(3) - (4)	$c_2 = \frac{a - a_2}{a_1 - a_2}$	0.7861	0.7886
(9)	(5) - (2)	$d_1 = \frac{b_1 - b}{b_1 - b_2}$	0.7717	0.7717
(10)	(5) - (6)	$d_2 = \frac{b - b_2}{b_1 - b_2}$	0.2283	0.2283
(11)	Table IV*	λ_{11}	2.318	←
(12)	Table IV*	λ_{12}	2.324	←
(13)	Table IV*	λ_{21}	2.310	←
(14)	Table IV*	λ_{22}	2.318	←
(15)	(8)(11) + (7)(13)	$c_2\lambda_{11} + c_1\lambda_{21}$	2.31629	2.31631
(16)	(8)(12) + (7)(14)	$c_2\lambda_{12} + c_1\lambda_{22}$	2.32272	2.32273
(17)	(10)(15) + (9)(16)	$\lambda(ab)$ $= d_2(c_2\lambda_{11} + c_1\lambda_{21})$ $+ d_1(c_2\lambda_{12} + c_1\lambda_{22})$	2.321	2.321

* For the given ϵ , λ is a function of f and t_0 and is given in Johnson and Welch's Table IV, for specified values of y (or y') and f (or $12/\sqrt{f}$). a and b are the values of the arguments (in this case y and $12/\sqrt{f}$, respectively) for which λ is required. a_1 , a_2 , b_1 , and b_2 are the values of the arguments for which Table IV gives λ values and between which we interpolate to find $\lambda(a,b)$. λ_{11} , λ_{12} , λ_{21} , and λ_{22} are the tabular values corresponding to a_1 , a_2 , b_1 , and b_2 . The following scheme explains the notation;

	...	b_1	b_2	...
...				
a_1		λ_{11}	λ_{12}	
a_2		λ_{21}	λ_{22}	
...				

The computation of the OC curve for the above plan is illustrated by finding the values of p for which L_p is 0.2 and 0.7. The figures given in Table 1.12 represent the calculations necessary to determine the values of p corresponding with these two values of L_p . Additional columns would be required for additional points on the OC curve.

TABLE 1.12
WORK SHEET 4 FOR OPERATING-CHARACTERISTIC CURVE

(1) Row number	(2) Operation	(3) Result	(4) First point	(5) Second point
(1)	Given	L_p	0.2	0.7
(2)	Smaller of L_p and $1 - L_p$	ϵ	0.2	0.3
(3)	Sheet 3, line 1, last column	a	0.52114	←
(4)	Sheet 3, line 2, last column	b	2.2283	←
(5)	Sheet 3, row 3*	a_1	0.6	0.5
(6)	Sheet 3, row 4*	a_2	0.5	0.6
(7)	Sheet 3, row 5	b_1	3.	←
(8)	Sheet 3, row 6	b_2	2.	←
(9)	(5) - (3)	$c_1 = \frac{a_1 - a}{a_1 - a_2}$	0.7886	0.2114
(10)	(5) - (6)	$c_2 = \frac{a - a_2}{a_1 - a_2}$	0.2114	0.7886
(11)	(3) - (6)	$d_1 = \frac{b_1 - b}{b_1 - b_2}$	0.7717	←
(12)	(7) - (8)	$d_2 = \frac{b - b_2}{b_1 - b_2}$	0.2283	←
(13)	Table IV†	λ_{11}	0.9125	0.4318
(14)	Table IV†	λ_{12}	0.8899	0.4632
(15)	Table IV†	λ_{21}	0.9192	0.4408
(16)	Table IV†	λ_{22}	0.8945	0.4691
(17)	(10)(13) + (9)(15)	$c_2\lambda_{11} + c_1\lambda_{21}$	0.91778	0.43370
(18)	(10)(14) + (9)(16)	$c_2\lambda_{12} + c_1\lambda_{22}$	0.89353	0.46445
(19)	(12)(17) + (11)(18)	$\lambda(ab)$ $= d_2(c_2\lambda_{11} + c_1\lambda_{21})$ $+ d_1(c_2\lambda_{12} + c_1\lambda_{22})$	0.8991	0.4574
(20)	Sheet 2, row 14, last column†	t_0	12.47223	-12.47223
(21)	Sheet 2, row 20, last column	$\sqrt{1 + \frac{t_0^2}{2f}}$	1.91886	←
(22)	(20) - (19) × (21)	$t_0 - \lambda \sqrt{1 + \frac{t_0^2}{2f}}$	10.74699	-13.34992
(23)	(22) if $\epsilon = L_p$ -(22) if $\epsilon = 1 - L_p$	δ	10.74699	13.34992
(24)	Sheet 1, row 5	\sqrt{N}	5.47723	←
(25)	(23) ÷ (24)	$U = \frac{\delta}{\sqrt{N}}$	1.96212	2.43735
(26)	Table 1.5	p	0.0249	0.0074

* The interchange of a_1 and a_2 in column (4) is made for consistency with the interpolation scheme of sheet 3.

† Use the panel of Table IV that corresponds with the value of ϵ given in row (2). Note that the portion of Table IV where t is positive is used for column (4) and the portion where t is negative is used for column (5).

If only N and u_0 are given and no preliminary calculations are available from work sheets for determining u_0 by the exact method, then sheet 4 must be supplemented by a sheet consisting of rows (14) through (24) of sheet 2, with t taken as $\sqrt{N}u_0$ and f taken as $N - 1$.

11.5. Construction of Table 1.2

Problem. Given: p_1 , p_2 , α , and β

Required: N and k

A single-sampling plan based on variables is defined by a sample size N and a value k , the multiple of the standard deviation in the criterion $\bar{x} + ks < U$ for accepting the lot, where U is the value above which the characteristic being inspected is regarded as defective. If no restrictions are imposed on sample size, a plan can be constructed for which the operating-characteristic curve will pass through two specified points. In practice, the first point often corresponds with a lot quality p_1 (AQL) for which it is desirable that the probability of rejection should be only α (producer's risk), and the second point corresponds with a lot quality p_2 (LTPD) for which it is desirable that the probability of acceptance should be only β (consumer's risk).

Consider the family of all OC curves that pass through the point $(p_1, 1 - \alpha)$ but which have differing values of N . If N is small these curves decline gradually as p increases from p_1 , and if N is large they decline sharply. There will be one OC curve among the family that passes closer than any other curve to the point (p_2, β) . Since N takes only integral values, there usually will be no curve that passes exactly through (p_2, β) . A curve could, however, be made to pass exactly through (p_2, β) if it were allowed to deviate from $(p_1, 1 - \alpha)$. Table 1.2 has been constructed in such a way that the OC curves generally pass not exactly through either $(p_1, 1 - \alpha)$ or (p_2, β) but very close to both. The distance of the OC curve from the intended two points has been measured horizontally, that is, by the difference between the actual and intended qualities for which the probabilities of acceptance are $1 - \alpha$ and β .

The values of N and k in Table 1.2 were obtained in three stages: (1) obtaining a first approximation to N and k ; (2) determining the degree to which the preliminary values of N and k satisfy the requirement that the OC curve pass through $(p_1, 1 - \alpha)$ and (p_2, β) ; and (3) adjusting N or k to improve the approximation.

Step 1. From p_1 , p_2 , α , and β , determine K_1 , K_2 , K_α , and K_β , the normal deviates exceeded with probabilities p_1 , p_2 , α , and β , respectively, as given by Table 1.1.

Step 2. Calculate the first approximation to k from

$$k = \frac{K_\alpha K_2 + K_\beta K_1}{K_\alpha + K_\beta}$$

Step 3. Calculate an approximate sample size N from

$$N = \frac{k^2 + 2}{2} \left(\frac{K_\alpha + K_\beta}{K_1 - K_2} \right)^2$$

Step 4. By the method given in Sec. 11.4 for determining the quality p corresponding to a specified probability of acceptance L_p , determine $p_{1-\alpha}$ and p_β where

$p_{1-\alpha}$ = the quality for which the probability of acceptance is $1 - \alpha$

p_β = the quality for which the probability of acceptance is β

If $p_{1-\alpha}$ and p_β are sufficiently close to p_1 and p_2 , respectively, then the values of k and N given by steps 2 and 3 define a satisfactory sampling plan.

Step 5. If the discrepancy between $p_{1-\alpha}$ and p_1 or that between p_β and p_2 is too large, determine a better plan by adjusting either N or k according to the following rules:

- a. If $p_{1-\alpha}$ is greater than p_1 and p_β is less than p_2 , take the next lower integer for N and the same k , and repeat step 4.
- b. If $p_{1-\alpha}$ is less than p_1 and p_β is greater than p_2 , take the next higher integer for N and the same k , and repeat step 4.
- c. If $p_{1-\alpha}$ is less than p_1 and p_β is less than p_2 , use the same N and a smaller value of k , and repeat step 6.
- d. If $p_{1-\alpha}$ is greater than p_1 and p_β is greater than p_2 , use the same N and a larger value of k , and repeat step 6.

These rules can be applied regardless of the method used for finding the first approximation to k and N . When these are found by steps 2 and 3, however, rule *d* will usually be applicable.

Calculate the better approximation for k mentioned in (c) and (d) from

$$k = \frac{\lambda_1 K_2 + \lambda_2 K_1}{\lambda_1 + \lambda_2}$$

where

λ_1 = value of λ computed in determining $p_{1-\alpha}$ in step 4

λ_2 = value of λ computed in determining p_β in step 4

Step 6. For the required N and k , take the pair of values for which $p_{1-\alpha}$ and p_β are close enough, or closest, to the given values of p_1 and p_2 , respectively.

Table 1.2, which gives values of N and k for various combinations of p_1 and p_2 when $\alpha = 0.05$ and $\beta = 0.10$, was constructed by essentially the method described above. For each plan in Table 1.2, except that for $p_1 = 0.05$ and $p_2 = 0.40$, the true values of p_1 and p_2 agree exactly with the intended values when rounded to the number of decimal places with which the intended p_1 and p_2 are given in the table; in many cases the agreement is much better. Minor improvements could, no doubt, be made in many cases.

11.6. Sequential Analysis of Proportion Defective by Variables*

The fact that

$$z = \bar{x} \mp ks \quad (230)$$

can be taken as approximately normally distributed with mean and standard deviation approximately

$$Z = \mu + k\sigma \quad (231)$$

and

$$\sigma(N) = \sigma P(N) \quad (232)$$

where

$$F(N) = \sqrt{\frac{1}{N} + \frac{k^2}{2(N-1)}} \quad (233)$$

may be made the basis of a sequential procedure for controlling percent defective by means of variables.

For a lot of acceptable quality, that is, one in which the mean of z is Z_1 as defined by (155), the probability density of z is given by

$$P(z|Z_1) = \frac{1}{\sigma(N)\sqrt{2\pi}} e^{-\frac{(z-Z_1)^2}{2\sigma^2(N)}} \quad (234)$$

Similarly, for a lot of unacceptable quality, that is, one in which the mean of z is Z_2 as defined by (156), the probability density of z is

$$P(z|Z_2) = \frac{1}{\sigma(N)\sqrt{2\pi}} e^{-\frac{(z-Z_2)^2}{2\sigma^2(N)}} \quad (235)$$

A sequential test is made by computing λ after each observation, where

$$\lambda = \log_e \frac{P(z|Z_2)}{P(z|Z_1)} \quad (236)$$

and rejecting the lot if

$$\lambda \geq a \quad (237)$$

accepting it if

$$\lambda \leq -b \quad (238)$$

* See Chap. 17 for a brief account of sequential analysis and for references to the fundamental work on this subject, the theory of which was developed in the Statistical Research Group by A. Wald. An exact treatment of proportion defective problems by sequential analysis of variables involves the ratio of densities of two non-central t distributions. Henry Goldberg has shown that this may be expressed in terms of a confluent hypergeometric function, tables of which were prepared for the Statistical Research Group by the New York Mathematical Tables Project in a form suitable for use in sequential analysis. There is in preparation an additional section for *Sequential Analysis* that will include these tables and an explanation of their use. The present section simply outlines a sequential procedure based on the approximations used elsewhere in this chapter for single sampling.

or taking another observation if

$$-b < \lambda < a \quad (239)$$

where

$$a = \log_e \frac{1 - \beta}{\alpha} \quad (240)$$

$$b = \log_e \frac{1 - \alpha}{\beta} \quad (241)$$

α being the probability of rejecting a lot of quality Z_1 and β the probability of accepting a lot of quality Z_2 . Each calculation of λ is based on all observations.

To obtain λ , we take the logarithm of (234) and subtract it from the logarithm of (235), which yields

$$\lambda = \frac{1}{2[\sigma(N)]^2} [(z - Z_1)^2 - (z - Z_2)^2] = \frac{Z_2 - Z_1}{[\sigma(N)]^2} \left(z - \frac{Z_1 + Z_2}{2} \right) \quad (242)$$

Substituting for Z_1 and Z_2 from (155) and (156) and for $\sigma(N)$ from (232), and rearranging, gives

$$\lambda = \frac{K_1 - K_2}{\sigma[F(N)]^2} \left[z - U - \sigma \left(k - \frac{K_1 + K_2}{2} \right) \right] \quad (243)$$

which may be rewritten as

$$z = U + \sigma \left[\frac{\lambda[F(N)]^2}{K_1 - K_2} - \frac{K_1 + K_2}{2} + k \right] \quad (244)$$

This will be independent of σ if

$$k = \frac{K_1 + K_2}{2} - \frac{\lambda[F(N)]^2}{K_1 - K_2} \quad (245)$$

On substituting for $F(N)$ from (233), there results a quadratic in k for which the solution is

$$k = \frac{\sqrt{1 - AB} - 1}{A} \quad (246)$$

where

$$A = \frac{\lambda}{(N - 1)(K_1 - K_2)} \quad (247)$$

and

$$B = \frac{2\lambda}{N(K_1 - K_2)} - (K_1 + K_2) \quad (248)$$

For each value of N , two values of k are obtained from (246), the first, k_r , by replacing λ in (247) and (248) by a , and the second, k_a , by

replacing λ by $-b$, where a and b are given by (240) and (241).^{*} Then after each observation both

$$z_R = \bar{x} + k_R s \quad (249)$$

and

$$z_A = \bar{x} + k_A s \quad (250)$$

are computed. If $z_R \geq U$ the lot is rejected. If $z_A \leq U$ the lot is accepted. If neither condition is fulfilled, another item is inspected, new values of \bar{x} , s , k_R , and k_A are computed from all the observations, and new values of z_R and z_A are compared with U .

An alternative computational procedure is to compute k_o after each observation, where

$$k_o = \frac{U - \bar{x}}{s} \quad (251)$$

then if $k_o \leq k_A$ the lot is accepted, if $k_o \geq k_R$ the lot is rejected, and if $k_A < k_o < k_R$ another item is inspected.

The values of k_A and k_R depend upon N , p_1 , p_2 , α , and β . In any one problem all of these but N are fixed, so a table showing k_A and k_R for various values of N can be prepared in advance. If $p_1 = 0.15$, $p_2 = 0.30$, $\alpha = 0.01$, $\beta = 0.02$, and $N = 95$, the values of k_R and k_A are 0.6651 and 0.8930, respectively.[†] For a single-sampling plan, the corresponding value of k was found in Sec. 4.2.2 to be 0.7645. For the sequential plan, if no decision had been reached from the first 94 observations, rejection would occur if for the first 95 observations $\bar{x} + 0.6651s \geq U$ and acceptance would occur if $\bar{x} + 0.8930 \leq U$; if neither condition were fulfilled, another observation would be made. From the data in Sec. 7.2.2, where $\bar{x} = 30.232$, $s = 5.000$, and $U = 35$, we find $z_R = 33.56$, which, being less than 35, does not call for rejection; and $z_A = 34.70$, which, being less than 35, calls for acceptance.

12. NOTATION

The arrangement is alphabetical, the sequence of listing under each letter being as follows: first Roman, then Greek letters; within these

^{*} Tables of a and b in terms of α and β are given in Statistical Research Group *Sequential Analysis*, Tables 4.2, 5.1, 6.1, and 7.31. These give a and b to 3 decimal places for values of α and β of 0.001, 0.01 to 0.05 by steps of 0.01, 0.05 to 0.20 by steps of 0.05, and 0.20 to 0.40 by steps of 0.10.

[†] From the unpublished tables referred to in the footnote at the beginning of Sec. 11.6, which are based on the likelihood ratio computed from two non-central t distributions, the corresponding values of k_A and k_R are found to be 0.6630 and 0.8893. For $k_R = 0.6651$ and $k_A = 0.8930$, the true values of α and β are, respectively, 0.0110 and 0.0177, which differ by 9.6 and 11.7 percent from the intended values, 0.01 and 0.02. Thus, these two OC points lie below (to the left of) those intended, whereas with single sampling the true points generally lie above (to the right of) those intended (see Table 1.8).

groups, first capital, then small letters; within these groups, first those without, then those with, primes, bars, or carets; within these groups, first those without subscripts, next those with literal subscripts (following the same sequence as for letters), and finally those with numerical subscripts (in numerical order). Certain symbols, notably a and b , are used in a variety of different meanings that occur only locally; in such cases the listing is in order of first appearance. Section 11.4 employs the notation of Johnson and Welch, which differs from (and in some respects, for example, U and L , contradicts) that used elsewhere in the chapter.

Symbol	See	Meaning
A	p. 37	An adjustment constant subtracted from each observation
A	p. 61	Critical value of z for accepting or rejecting a lot
A	p. 84	A function of λ , N , K_1 , and K_2 that appears in formulas for the sequential procedure
AQL	equations (246), (247)	Acceptable quality level (see p_1)
a	pp. 11, 45	Function of N and K_a that appears in the formula for k when N is fixed
a	pp. 19, 20	Function of K_1 , K_2 , K_a , and K_β that appears in the formula for N
a	equations (21), (22)	Coefficient of quadratic term in condition, quadratic in X , for acceptance in terms of Y
a	p. 61	Multiple of σ in formula for mean of distribution of s
a	p. 35	A critical value of λ in a sequential test on the basis of which the lot is rejected or another observation is taken
a	equations (55), (56)	Producer's risk. Probability that a lot of acceptable quality (p_1 or AQL) will be rejected
B	p. 58	A function of λ , N , K_1 , and K_2 that appears in formulas for the sequential procedure
b	equation (118)	Function of N , K_1 , and K_a that appears in the formula for k when N is fixed
b	pp. 83, 84	Negative of coefficient of linear term in condition, quadratic in X , for acceptance in terms of Y
b	equation (240)	Multiple of $\sigma/\sqrt{2(N-1)}$ in the formula for standard deviation of distribution of s
α	p. 16	Function of k and a that appears in the formula for N
B	p. 84	A critical value of λ in a sequential test on the basis of which the lot is accepted or another observation is taken
b	equations (246), (248)	
b	pp. 19, 20	
b	equations (21), (23)	
b	p. 35	
b	equations (55), (57)	
b	p. 58	
b	equation (119)	
b	p. 61	
b	equations (136), (138)	
b	pp. 83, 84	
b	equation (241)	

Symbol	See	Meaning
b_M	pp. 53, 54 equations (100), (103)	Value of b obtained from equation (57) by replacing U by M
b_U	pp. 53, 54 equations (100), (103)	Same as b given by equation (57); subscript U used to distinguish b_U from b_M
b'	p. 41 equations (78), (79)	Negative of coefficient of linear term in condition, linear in X , for acceptance in terms of Y
β	p. 16	Consumer's risk. Probability that a lot of unacceptable quality (p_2 or LTPD) will be accepted
c	p. 35 equations (55), (58)	Constant term in condition, quadratic in X , for acceptance in terms of Y
c_M	pp. 53, 54 equation (104)	Value of c obtained from equation (58) by replacing U by M
c_U	pp. 53, 54 equations (100), (104)	Same as c given by equation (58); subscript U used to distinguish c_U from c_M
c'	p. 41 equations (78), (80)	Constant term in condition, linear in X , for acceptance in terms of Y
γ	p. 43	A proportion ($0 \leq \gamma \leq 1$) denoting a confidence coefficient
γ_c	p. 44	Confidence coefficient used in judging whether to continue normal inspection
γ_r	p. 44	Confidence coefficient used for judging whether to resume normal inspection
δ	p. 73	Johnson and Welch notation for a constant appearing in the numerator of non-central t ; $\delta = \sqrt{N}U$
$\delta(f, t_0, \epsilon)$	p. 73 Sec. 11.4.4	Johnson and Welch notation for the value of δ that makes $P(f, \delta, t_0) = \epsilon$
ϵ	p. 17 equation (9)	A probability ($0 \leq \epsilon \leq 1$); probability that a normal deviate will exceed K_ϵ
ϵ	p. 73	Johnson and Welch notation for probability of acceptance
$F(N)$	p. 61	Any function of N that is independent of σ
f	p. 73	Degrees of freedom of χ^2
h	p. 42	Number of lots from which samples are taken and combined into one large sample for the purpose of computing the process average
K	p. 9	$(U - \mu)/\sigma$. That is, the difference between the upper limit and the population mean, as a multiple of the population standard deviation
K_α	p. 17	Normal deviate exceeded with probability α
K_β	p. 17	Normal deviate exceeded with probability β
K_ϵ	p. 17	Normal deviate exceeded with probability ϵ

Symbol	See	Meaning
K_0	p. 21	Normal deviate exceeded with probability p_0
K_1	p. 17	Normal deviate exceeded with probability p_1
K_2	p. 17	Normal deviate exceeded with probability p_2
k	p. 12	Coefficient of the sample standard deviation in the acceptance criterion $\bar{x} + ks \leq U$; also, acceptable level of statistic k_0
k_A	p. 84	Acceptance level for k_0 in a sequential test
k_0	p. 43	$(U - \bar{x})/s$. That is, the observed difference between U and the sample mean in units of the sample standard deviation; sample estimate of K
k_R	p. 84	Rejection level for k_0 in a sequential test
k'	p. 48	\sqrt{n} times the coefficient of the sample standard deviation in the acceptance criterion, $\bar{x} + (k'/\sqrt{n}) s \leq U'$, used when items are eventually assembled in sets of n
k_γ	p. 47	Upper confidence limit for K , based on a confidence coefficient of γ
$k_{\gamma_0}, k_{\gamma_0}$	p. 45	Lower and upper limits, respectively, between which a computed value of k_0 leads under normal inspection to continuing normal inspection, based on a confidence coefficient of γ
$k_{\gamma_1}, k_{\gamma_1}$	p. 45	Lower and upper limits, respectively, between which a computed value of k_0 leads under reduced or tightened inspection to resuming normal inspection, based on a confidence coefficient γ
L	p. 72	Johnson and Welch notation for the upper limit of a variable, above which an item is defective; corresponds with our U
LTPD	pp. 22, 45	Lot tolerance percent defective (see p_2)
L_p	p. 15	Ordinate of an OC curve at abscissa p . The probability that a lot of fraction defective p will, if submitted to a given acceptance test, be passed
$L_{\mu, \sigma}$	p. 16	Value of an OC curve at μ, σ . The probability that a lot of mean μ and standard deviation σ will, if submitted to a given acceptance test, be passed
L_1	p. 61	Probability that a lot having mean Z_1 will, if submitted to a given acceptance test, be passed

Symbol	See	Meaning
L_2	p. 62	Probability that a lot having mean Z_2 will, if submitted to a given acceptance test, be passed
λ	p. 83	Natural logarithm of the ratio of two probability densities, computed after each observation in a sequential test
$\lambda = \lambda(f, t_0, \epsilon)$	p. 74 equations (223), (224)	Johnson and Welch notation for a function of f , t_0 , and ϵ used in the calculation of $\delta(f, t_0, \epsilon)$ and $t(f, \delta, \epsilon)$
λ_1	p. 82	Value of λ computed in determining p_{1-a}
λ_2	p. 82	Value of λ computed in determining p_β
M	p. 13	Minimum value of a variable, below which an item is defective
μ	p. 9	Population mean of a normally distributed variable
μ'	p. 41	Best estimate of \bar{x} available before the sample is inspected
N	p. 12	Number of items in a sample
N_a	p. 26	Sample size for single-sampling plan for percent defective based on attributes
N_i ($i = 1, \dots, h$)	p. 43	Number of items in the i th sample of a group of h samples
N_m	p. 27	Sample size for single-sampling plan for percent defective based on the mean when the standard deviation is known
N_s	p. 28	Sample size for single-sampling plan for percent defective based on the standard deviation when the mean is known
N_t	p. 27	Sample size for single-sampling plan for percent defective based on the mean and standard deviation when both are unknown but estimated from sample
N'	p. 48	Number of sets of n items in a sample
n	p. 48	Number of items constituting a set which is judged defective or not on the basis of the average for the set
n	p. 50	Number of variables upon which the quality of an item depends
OC	Sec. 3.4 Sec. 6	Operating characteristics. The probability that a given acceptance test will pass lots of various qualities if submitted
PA	p. 42	Process average percent defective
$P(f, \delta, t_0)$	p. 73	Johnson and Welch notation for the probability that t exceeds a given level t_0 for given f and δ
$P(z Z_1)$	p. 83 equation (234)	Probability density of z for lot in which the mean of z is Z_1
$P(z Z_2)$	p. 83 equation (235)	Probability density of z for lot in which the mean of z is Z_2

Symbol	See	Meaning
Y_E	p. 36 equation (70)	Boundary between error and acceptance regions when values of X are plotted horizontally and values of Y vertically; minimum value of Y that can be obtained for any given value of X
Y_R	p. 36	Boundary between rejection and acceptance regions when values of X are plotted horizontally and values of Y vertically; parabola defined by equation (55), using the equality sign
Y'	p. 37 equation (71)	Sum of squares of adjusted observations, that is, observations from which a constant has been subtracted
Y'_E	p. 37 equation (74)	Boundary between the error and acceptance regions when values of X are plotted horizontally and values of Y' vertically
Y'_R	p. 37 equation (73)	Boundary between the rejection and acceptance regions when values of X are plotted horizontally and values of Y' vertically
\bar{Y}_R	p. 67 equation (184)	Minimum value of the curve Y_R ; a value of Y below which the lot is acceptable without regard to X
\bar{Y}'_R	p. 69 equation (195)	Minimum value of the curve Y'_R ; a value of Y' below which the lot is acceptable without regard to X
y	p. 74 equation (225)	Johnson and Welch notation for a function of t_0 and f , one of the arguments against which λ is tabled
y'	p. 74 equation (226)	Johnson and Welch notation for a function of t_0 and f , one of the arguments against which λ is tabled
Z	p. 61	Population mean of the normally distributed variable z
Z_1	p. 61	Value for Z for which it is required that the probability of rejection be α
Z_2	p. 61	Value of Z for which it is required that the probability of acceptance be β
z	p. 61	A normally distributed variable
z	p. 73	Johnson and Welch notation for a variable distributed normally about zero with unit standard deviation
z_A	p. 85	$\bar{x} + k_{AS}$
z_R	p. 85	$\bar{x} + k_{RS}$

13. REFERENCES

- American Society for Testing Materials: *Manual of Presentation of Data*, Philadelphia, 1941.
- American Standards Association: *Control Chart Method of Controlling Quality during Production*, New York, 1942, 41 pp.
- CUMRIE, L. J., editor: *Barlow's Tables of Squares, Cubes, Square Roots, Cube Roots, and Reciprocals of All Integral Numbers up to 12,500*, 4th ed., E. & F. N. Spon, Ltd., London, and Chemical Publishing Company of New York, Inc., New York, 1911, 258 + xii pp.
- CRAIG, CECIL C.: "Note on the Distribution of Non-central t with an Application," *Annals of Mathematical Statistics*, Vol. 12 (1941), pp. 224-228.
- DODGE, HAROLD F., and ROMIG, HARRY G.: *Sampling Inspection Tables: Single and Double Sampling*, John Wiley & Sons, Inc., New York, 1944, 106 + vi pp.
- FISHER, RONALD A., and YATES, FRANK: *Statistical Tables for Biological, Agricultural and Medical Research*, 2d ed., Oliver and Boyd, Ltd., London and Edinburgh, 1943, 98 + viii pp.
- JENNETT, W. J., and WELCH, B. L.: "The Control of Proportion Defective As Judged by a Single Quality Characteristic Varying on a Continuous Scale," *Supplement to the Journal of the Royal Statistical Society*, Vol. 6 (1939), pp. 80-88.
- JOHNSON, N. L., and WELCH, B. L.: "Applications of the Non-central t -Distribution," *Biometrika*, Vol. 31 (1940), pp. 362-389.
- KELLEY, TRUMAN LEE: *The Kelley Statistical Tables*, The Macmillan Company, New York, 1938, 136 pp.
- Mathematical Tables Project, Work Projects Administration for the City of New York, Federal Works Agency: *Tables of Probability Functions*, Vol. 2, National Bureau of Standards, Washington, D.C., 1942, 344 + xxi pp.
- PEACH, PAUL: *An Introduction to Industrial Statistics and Quality Control*, J. B. Phillips Company, Raleigh, N. C., 1945, 142 pp.
- PRZYBOROWSKI, J., and WILEŃSKI, H.: "Statistical Principles of Routine Work in Testing Clover Seed for Dodder," *Biometrika*, Vol. 27 (1935), pp. 273-292.
- ROMIG, HARRY G.: *Allowable Average in Sampling Inspection*, privately printed doctoral thesis, Columbia University, 1939, 58 pp.
- SHEWHART, WALTER A.: *Economic Control of Quality of Manufactured Product*, D. Van Nostrand Company, Inc., New York, 1931, 501 + xiv pp.
- , with the editorial assistance of DEMING, W. EDWARDS: *Statistical Method from the Viewpoint of Quality Control*, Graduate School, U.S. Department of Agriculture, Washington, D. C., 1939, 155 + ix pp.
- Statistical Research Group, Columbia University: *Sampling Inspection: Principles, Procedures, and Tables for Single, Double, and Sequential Sampling in Acceptance Inspection and Quality Control*, McGraw-Hill Book Company, Inc., New York, 1947.
- : *Sequential Analysis of Statistical Data: Applications*, rev. ed., Columbia University Press, New York, 1945.

CHAPTER 2

TOLERANCE LIMITS FOR NORMAL DISTRIBUTIONS

	PAGE
1. Nature of Tolerance Limits	97
1.1 <i>Definition of Tolerance Limits</i>	97
1.2 Class of Tolerance Limits Considered	97
1.3 Other Kinds of Limits.	98
1.3.1 <i>One-sided Tolerance Limits</i>	98
1.3.2 Multivariate Tolerance Limits.	99
1.3.3 Tolerance Limits for Non-normal Distributions	99
1.3.4 Distribution-free Tolerance Limits	99
1.3.5 Confidence Limits	99
2. Table of Factors for Tolerance Limits.	100
2.1 Description.	100
2.2 Use of the Table: Example	100
2.3 Cases outside the Range of the Table	101
2.3.1 Formula for Large Values of N	101
2.3.2 Example	101
3. Construction of the Table.	108
3.1 Formula.	108
3.2 Basic Network of Points.	108
3.3 Percentage Points of χ^2	108
3.4 Computation of r	109
4. References.	109

TABLES

2.1 Tolerance Factors for Normal Distributions.	102
2.2 Coefficients to Facilitate the Use of Formula (6) for Computing K When N Is Large	108

This chapter was prepared by
Albert H. Bowker, Stanford University

CHAPTER 2

TOLERANCE LIMITS FOR NORMAL DISTRIBUTIONS

1. NATURE OF TOLERANCE LIMITS

1.1. Definition of Tolerance Limits

A common method of specifying the quality of manufactured product is to set a range, the bounds of which are called "*tolerance limits*," such that a certain percentage of the product made under commercial conditions may be expected to have a quality falling between the limits. For example, tolerance limits may be placed on dimensions to indicate the extent of interchangeability of parts. Tolerance limits are also used in other fields, for example medicine and psychology, to indicate the range of normal variation in various characteristics. In general, tolerance limits are limits within which lie a certain percentage of the individuals of a statistical universe.

The satisfactory application of tolerance limits requires that assignable causes of variability be detected and eliminated so that the remaining variability may be considered random. In other words, prediction from past data of the proportion of future observations that will be contained within fixed limits assumes that the successive values of the quality characteristic in question may be considered randomly chosen from a statistical universe.*

1.2. Class of Tolerance Limits Considered

The tolerance limits considered in this chapter are symmetrical about the mean, and they are based on the assumption that the underlying statistical universe may be described by a normal distribution. When the true mean and standard deviation μ and σ of this normal distribution are known, tolerance limits are formed by adding to and subtracting from the mean a certain multiple K of the standard deviation; the appropriate multiple is easily obtained from tables of the normal distribution and depends only upon what proportion of the universe is to be included within the limits.† Values of K corresponding to various proportions

* A detailed discussion of the nature, use, and practical basis for tolerance limits may be found in Shewhart, *Statistical Method*, Chap. II, pp. 50-79. In fact, this is the original source on which subsequent work on tolerance limits has been based. (For full citations, see Sec. 4.)

† See Chap. 1, Sec. 2, for further discussion of this point.

included within the tolerance range may be found by entering Table 1.1 of Chap. 1 with ϵ equal to half the proportion excluded. For example, 90 percent of the population is included in the interval $\mu - 1.645\sigma$ to $\mu + 1.645\sigma$, since 90 percent inclusion corresponds with 10 percent exclusion, or $\epsilon = 0.05$.

In most practical situations the true values μ and σ are not known, and tolerance limits must be estimated from the mean \bar{X} and the standard deviation s of a sample of N observations. While the limits $\mu \pm 1.645\sigma$ will include 90 percent of the universe, clearly the same assertion cannot be made of the limits $\bar{X} \pm 1.645s$. The proportion included between the limits $\bar{X} \pm Ks$ depends, for example, on whether the sample mean is unusually large, reasonably close to the population mean, or unusually small. The sample standard deviation is also subject to chance fluctuations that affect the proportion included between the limits. In fact, if a value of K is fixed, no two samples from a given universe will lead to the same tolerance limits, since both \bar{X} and s will vary from sample to sample.

It is clear then that the proportion of the universe included between the limits $\bar{X} \pm Ks$ is a random variable, and that it is impossible to determine K so that the limits will always contain a specified proportion P of the universe. It is possible, however, to determine K in such a way that in a large series of samples from normal universes a certain proportion γ of the intervals $\bar{X} \pm Ks$ will include P or more of the universe; γ is called "the confidence coefficient," since it is a measure of the confidence with which we may assert that a given tolerance range includes at least P of the universe.

Intuitively, it seems reasonable that the values of K for use with sample means and standard deviations will be somewhat larger than the values used if the true mean and standard deviation are known. In fact, by taking K very large the probability that the interval $\bar{X} \pm Ks$ will contain at least P of the universe may be made as close to $\frac{1}{2}$ as is desired. Since the length of the tolerance interval is $2Ks$, the smaller K is, the more meaningful and the less trivial a tolerance range is. The position is, therefore, one of being able to state broad generalities with little risk of error, or to make more precise statements at greater risk. The problem is to find the smallest factor K that may be associated with a specified confidence coefficient γ , proportion P , and sample size N . Table 2.1 presents such factors for various combinations of γ , P , and N . Before discussing the use of Table 2.1, it is desirable to contrast the tolerance limits it yields with other kinds of limits.

1.3. Other Kinds of Limits

1.3.1. One-sided Tolerance Limits.—Instead of specifying a two-sided interval that will contain a certain percentage of the product, it

will frequently be appropriate to specify a one-sided limit such that a fixed percentage of the product will have a quality greater than (or a quality less than, as the case may be) this limit. Problems of this sort may be solved by the methods of Chap. 1, Sec. 9.2.

1.3.2. Multivariate Tolerance Limits.—Certain methods of setting tolerance limits have been generalized by Wald and by Paulson to the problem of setting simultaneous limits on several quality characteristics of a single item. In this connection, see also Chap. 3.

1.3.3. Tolerance Limits for Non-normal Distributions.—Wald has considered the problem of setting tolerance limits on the basis of large samples for distributions of any known form, normal or otherwise. Application of these tolerance limits to normal distributions gives unsatisfactory results; their applicability (as contrasted with their theoretical correctness when N approaches infinity) to other forms of distribution has not been determined.

1.3.4. Distribution-free Tolerance Limits.—Sometimes it is desirable to set tolerance limits without making any assumption about the form, normal or otherwise, of the underlying distribution. Problems of this sort have been discussed by Wilks and by Wald. The problem of deciding whether to use tolerance limits based on the normal distribution, those based on some other distribution, or those which involve no assumption about the form of the distribution is one which, though of a kind common in applied statistics, has no satisfactory solution. Tolerance limits based on the normal distribution are substantially shorter for a fixed sample size than those based on no assumption about the distribution; but they may be irrelevant if the underlying distribution is too far from normal. The decision about the adequacy of the normality assumption may be based upon an analysis of measurements of a large number of items; it may be supported by theoretical considerations, for example, when the quality characteristic is known to be determined by many chance causes whose effects are essentially additive; or it may rest on a combination of theoretical and empirical evidence. It should be noted that if there is a stable universe from which the measurements are random observations, limits of the form $\bar{X} \pm Ks$ will, in a fraction γ of samples, include a certain proportion P' or more of the universe, where P' differs from the intended P by an amount depending upon the departure of the true distribution from normality.*

1.3.5. Confidence Limits.—Tolerance limits should not be confused with confidence limits (or with fiducial limits) for the mean or other parameters of the distribution. Confidence limits for the mean, which also are of the form $\bar{X} \pm Ks$, are computed in such a way that in a fraction γ of the samples from which they are computed they will include the mean

* For a fuller and more precise statement of this point, see Chap. 1, Sec. 9.4, including the quotation from Jennett and Welch.

TABLE 2.1

TOLERANCE FACTORS FOR NORMAL DISTRIBUTIONS

Factors K such that the probability is γ that at least a proportion P of the distribution will be included between $\bar{X} \pm Ks$, where \bar{X} and s are estimates of the mean and the standard deviation computed from a sample of N .

$\frac{P}{N}$	$\gamma = 0.75$					$\gamma = 0.90$					$\gamma = 0.95$					$\gamma = 0.99$				
	0.75	0.90	0.95	0.99	0.999	0.75	0.90	0.95	0.99	0.999	0.75	0.90	0.95	0.99	0.999	0.75	0.90	0.95	0.99	0.999
2	4.408	6.301	7.414	9.531	11.920	11.407	15.378	18.800	24.167	30.277	22.856	32.019	37.674	48.480	60.573	114.363	160.193	188.491	242.300	303.054
3	2.501	3.539	4.187	5.431	6.844	4.132	5.847	6.919	8.973	11.309	5.922	8.390	9.916	12.861	16.208	13.378	18.930	22.401	29.055	36.616
4	2.035	2.892	3.431	4.471	5.657	2.932	4.166	4.943	6.440	8.149	3.779	5.360	6.370	8.299	10.502	8.014	9.398	11.150	14.527	18.883
5	1.825	2.599	3.066	4.033	5.117	2.454	3.494	4.152	5.423	6.879	3.002	4.275	5.079	6.634	8.415	4.043	5.612	7.855	10.260	13.015
6	1.704	2.420	2.889	3.779	4.802	2.106	3.131	3.723	4.870	6.188	2.604	3.712	4.414	5.775	7.337	3.743	5.337	7.345	9.301	10.548
7	1.624	2.318	2.757	3.611	4.593	2.034	2.962	3.452	4.521	5.750	2.361	3.369	4.007	5.248	6.676	3.233	4.613	5.488	7.187	9.142
8	1.568	2.238	2.653	3.491	4.444	1.921	2.743	3.284	4.378	5.446	2.197	3.138	3.732	4.891	6.220	2.905	4.147	4.936	6.488	8.234
9	1.525	2.178	2.593	3.400	4.330	1.859	2.626	3.125	4.098	5.098	2.078	2.967	3.532	4.631	5.899	2.677	3.822	4.550	5.966	7.600
10	1.492	2.131	2.537	3.328	4.241	1.775	2.535	3.018	3.959	5.016	1.987	2.839	3.370	4.433	5.649	2.508	3.582	4.285	5.594	7.129
11	1.465	2.093	2.493	3.271	4.169	1.724	2.403	2.863	3.788	4.792	1.858	2.737	3.259	4.277	5.452	2.378	3.397	4.045	5.308	6.766
12	1.443	2.062	2.456	3.223	4.110	1.683	2.404	2.863	3.758	4.762	1.838	2.655	3.162	4.150	5.291	2.274	3.250	3.870	5.079	6.477
13	1.425	2.036	2.424	3.183	4.069	1.648	2.355	2.805	3.682	4.697	1.810	2.587	3.081	4.044	5.158	2.190	3.130	3.727	4.893	6.240
14	1.409	2.013	2.398	3.148	4.016	1.619	2.314	2.759	3.618	4.615	1.770	2.529	3.012	3.955	5.045	2.120	3.029	3.608	4.737	6.043
15	1.395	1.994	2.375	3.118	3.979	1.594	2.278	2.713	3.562	4.545	1.735	2.480	2.954	3.878	4.949	2.060	2.945	3.507	4.605	5.876
16	1.383	1.977	2.355	3.092	3.946	1.572	2.246	2.676	3.514	4.484	1.705	2.437	2.903	3.814	4.865	2.009	2.872	3.421	4.492	5.732
17	1.372	1.962	2.337	3.069	3.917	1.552	2.219	2.643	3.471	4.430	1.679	2.400	2.858	3.764	4.791	1.965	2.808	3.345	4.393	5.607
18	1.363	1.948	2.321	3.048	3.891	1.535	2.194	2.614	3.433	4.382	1.655	2.390	2.819	3.702	4.725	1.926	2.753	3.279	4.307	5.497
19	1.355	1.936	2.307	3.030	3.867	1.520	2.172	2.588	3.399	4.339	1.635	2.337	2.783	3.650	4.667	1.891	2.703	3.221	4.230	5.399
20	1.347	1.925	2.294	3.013	3.846	1.506	2.152	2.564	3.368	4.300	1.616	2.310	2.752	3.615	4.614	1.860	2.659	3.168	4.161	5.312
21	1.340	1.915	2.282	2.998	3.827	1.493	2.135	2.543	3.340	4.264	1.599	2.286	2.733	3.577	4.567	1.833	2.620	3.121	4.100	5.234
22	1.334	1.906	2.271	2.984	3.809	1.482	2.118	2.524	3.315	4.232	1.584	2.264	2.697	3.543	4.525	1.808	2.584	3.078	4.044	5.163
23	1.328	1.898	2.261	2.971	3.793	1.471	2.103	2.506	3.292	4.203	1.570	2.244	2.673	3.512	4.484	1.785	2.551	3.040	3.993	5.098
24	1.322	1.891	2.252	2.959	3.778	1.462	2.089	2.489	3.270	4.176	1.557	2.225	2.651	3.483	4.447	1.764	2.522	3.004	3.947	5.039
25	1.317	1.883	2.244	2.948	3.764	1.453	2.077	2.474	3.251	4.151	1.545	2.208	2.631	3.457	4.413	1.745	2.494	2.972	3.904	4.985
26	1.313	1.877	2.236	2.938	3.751	1.444	2.065	2.460	3.232	4.127	1.534	2.193	2.612	3.432	4.382	1.727	2.469	2.941	3.865	4.935
7	1.309	1.871	2.229	2.929	3.740	1.437	2.054	2.447	3.215	4.106	1.523	2.178	2.595	3.409	4.353	1.711	2.446	2.914	3.828	4.888

TABLE 2.1

TOLERANCE LIMITS

103

28	1.305	1.865	2.222	2.920	3.728	1.430	2.044	2.435	3.199	4.085	1.514	2.164	2.579	3.398	4.326	1.695	2.424	2.888	3.794	4.845
29	1.301	1.860	2.216	2.911	3.718	1.423	2.034	2.424	3.184	4.060	1.505	2.152	2.564	3.368	4.301	1.681	2.404	2.864	3.763	4.805
30	1.297	1.855	2.210	2.904	3.708	1.417	2.025	2.413	3.170	4.049	1.497	2.140	2.549	3.350	4.278	1.668	2.385	2.841	3.733	4.768
31	1.294	1.850	2.204	2.896	3.699	1.411	2.017	2.403	3.157	4.032	1.489	2.129	2.536	3.332	4.256	1.656	2.367	2.820	3.706	4.732
32	1.291	1.846	2.199	2.890	3.690	1.405	2.009	2.393	3.145	4.016	1.481	2.118	2.524	3.316	4.235	1.644	2.351	2.801	3.680	4.699
33	1.288	1.842	2.194	2.883	3.682	1.400	2.001	2.385	3.133	4.001	1.475	2.108	2.512	3.300	4.215	1.633	2.335	2.782	3.656	4.668
34	1.285	1.838	2.189	2.877	3.674	1.395	1.994	2.376	3.122	3.987	1.468	2.099	2.501	3.286	4.197	1.623	2.320	2.764	3.632	4.639
35	1.283	1.834	2.185	2.871	3.667	1.390	1.988	2.368	3.112	3.974	1.462	2.090	2.490	3.272	4.179	1.613	2.306	2.748	3.611	4.611
36	1.280	1.830	2.181	2.866	3.660	1.386	1.981	2.361	3.102	3.961	1.455	2.081	2.479	3.258	4.161	1.604	2.293	2.732	3.590	4.585
37	1.278	1.827	2.177	2.860	3.653	1.381	1.975	2.353	3.092	3.949	1.450	2.073	2.470	3.246	4.146	1.595	2.281	2.717	3.571	4.560
38	1.275	1.824	2.173	2.855	3.647	1.377	1.969	2.346	3.083	3.935	1.446	2.068	2.464	3.237	4.134	1.587	2.269	2.703	3.552	4.537
39	1.273	1.821	2.169	2.850	3.641	1.374	1.964	2.340	3.073	3.927	1.441	2.060	2.455	3.226	4.120	1.579	2.257	2.690	3.534	4.514
40	1.271	1.818	2.166	2.846	3.635	1.370	1.959	2.334	3.066	3.917	1.435	2.052	2.445	3.213	4.104	1.571	2.247	2.677	3.518	4.493
41	1.269	1.815	2.162	2.841	3.629	1.366	1.954	2.328	3.059	3.907	1.430	2.045	2.437	3.202	4.090	1.564	2.236	2.665	3.502	4.472
42	1.267	1.812	2.159	2.837	3.624	1.363	1.949	2.322	3.051	3.897	1.426	2.039	2.429	3.192	4.077	1.557	2.227	2.653	3.486	4.453
43	1.266	1.810	2.156	2.833	3.619	1.360	1.944	2.316	3.044	3.888	1.422	2.033	2.422	3.183	4.065	1.551	2.217	2.642	3.472	4.434
44	1.264	1.807	2.153	2.829	3.614	1.357	1.940	2.311	3.037	3.879	1.418	2.027	2.415	3.173	4.053	1.545	2.208	2.631	3.458	4.416
45	1.262	1.805	2.150	2.825	3.609	1.354	1.935	2.306	3.030	3.871	1.414	2.021	2.408	3.165	4.042	1.539	2.200	2.621	3.444	4.399
46	1.261	1.802	2.148	2.822	3.605	1.351	1.931	2.301	3.023	3.863	1.410	2.016	2.402	3.156	4.031	1.533	2.192	2.611	3.431	4.383
47	1.259	1.800	2.145	2.819	3.600	1.348	1.927	2.297	3.018	3.855	1.406	2.011	2.396	3.148	4.021	1.527	2.184	2.602	3.419	4.367
48	1.258	1.798	2.143	2.815	3.596	1.345	1.924	2.292	3.012	3.847	1.403	2.006	2.390	3.140	4.011	1.522	2.176	2.593	3.407	4.352
49	1.256	1.796	2.140	2.812	3.592	1.343	1.920	2.288	3.006	3.840	1.399	2.001	2.384	3.133	4.002	1.517	2.169	2.584	3.396	4.337
50	1.255	1.794	2.138	2.809	3.588	1.340	1.916	2.284	3.001	3.833	1.396	1.996	2.379	3.126	3.993	1.512	2.162	2.576	3.385	4.323
51	1.253	1.792	2.135	2.806	3.584	1.338	1.913	2.279	2.995	3.826	1.393	1.992	2.373	3.119	3.984	1.507	2.155	2.568	3.374	4.310
52	1.252	1.790	2.133	2.803	3.581	1.336	1.910	2.276	2.990	3.820	1.390	1.988	2.368	3.112	3.975	1.503	2.148	2.560	3.364	4.297
53	1.251	1.789	2.131	2.801	3.577	1.334	1.907	2.272	2.985	3.813	1.387	1.984	2.363	3.106	3.967	1.498	2.142	2.552	3.354	4.284
54	1.250	1.787	2.129	2.798	3.574	1.331	1.904	2.269	2.981	3.807	1.384	1.980	2.359	3.100	3.959	1.494	2.136	2.545	3.344	4.272
55	1.249	1.785	2.127	2.795	3.571	1.329	1.901	2.265	2.976	3.801	1.382	1.976	2.354	3.094	3.951	1.490	2.130	2.538	3.335	4.260
56	1.247	1.784	2.125	2.793	3.567	1.327	1.898	2.261	2.972	3.796	1.379	1.972	2.350	3.088	3.944	1.486	2.124	2.531	3.326	4.249
57	1.246	1.782	2.123	2.790	3.564	1.325	1.895	2.258	2.967	3.790	1.377	1.968	2.345	3.082	3.937	1.482	2.119	2.524	3.316	4.238
58	1.245	1.781	2.122	2.788	3.561	1.323	1.892	2.255	2.963	3.785	1.374	1.965	2.341	3.076	3.930	1.478	2.113	2.518	3.309	4.227
59	1.244	1.779	2.120	2.786	3.558	1.322	1.890	2.252	2.959	3.779	1.372	1.961	2.337	3.071	3.923	1.474	2.108	2.512	3.301	4.216
60	1.243	1.778	2.118	2.784	3.556	1.320	1.887	2.248	2.955	3.774	1.369	1.958	2.333	3.066	3.916	1.471	2.103	2.506	3.293	4.206
61	1.242	1.777	2.117	2.781	3.553	1.318	1.885	2.243	2.951	3.769	1.367	1.955	2.329	3.061	3.909	1.467	2.098	2.500	3.285	4.196
62	1.241	1.775	2.115	2.779	3.550	1.316	1.882	2.243	2.947	3.765	1.365	1.951	2.325	3.056	3.903	1.464	2.093	2.494	3.278	4.187
63	1.240	1.774	2.113	2.777	3.548	1.315	1.880	2.240	2.944	3.760	1.363	1.948	2.322	3.051	3.897	1.461	2.089	2.489	3.271	4.178
64	1.240	1.772	2.112	2.775	3.545	1.313	1.878	2.237	2.940	3.755	1.361	1.945	2.318	3.046	3.891	1.458	2.084	2.483	3.264	4.169

TABLE 2.1.—(Continued)

P N	$\gamma = 0.75$				$\gamma = 0.90$				$\gamma = 0.95$				$\gamma = 0.99$			
	0.75	0.90	0.95	0.99	0.75	0.90	0.95	0.99	0.75	0.90	0.95	0.99	0.75	0.90	0.95	0.99
65	1.239	1.771	2.110	2.773	3.543	1.312	1.875	2.235	2.937	3.751	1.359	1.943	1.455	2.080	2.478	3.257
66	1.238	1.770	2.109	2.771	3.540	1.310	1.873	2.232	2.933	3.747	1.357	1.940	1.452	2.076	2.473	3.250
67	1.237	1.769	2.108	2.770	3.538	1.309	1.871	2.229	2.930	3.742	1.355	1.937	1.449	2.071	2.468	3.244
68	1.236	1.768	2.106	2.768	3.536	1.307	1.869	2.227	2.927	3.738	1.353	1.934	1.446	2.067	2.463	3.237
69	1.235	1.766	2.105	2.766	3.533	1.306	1.867	2.225	2.923	3.734	1.351	1.932	1.443	2.063	2.459	3.231
70	1.235	1.765	2.104	2.764	3.531	1.304	1.865	2.222	2.920	3.730	1.349	1.929	1.440	2.060	2.454	3.225
71	1.234	1.764	2.102	2.763	3.529	1.303	1.863	2.220	2.917	3.727	1.347	1.927	1.438	2.056	2.450	3.219
72	1.233	1.763	2.101	2.761	3.527	1.302	1.861	2.218	2.915	3.725	1.345	1.924	1.435	2.052	2.445	3.214
73	1.233	1.762	2.100	2.760	3.525	1.300	1.859	2.216	2.912	3.719	1.344	1.922	1.433	2.049	2.441	3.208
74	1.232	1.761	2.099	2.758	3.523	1.299	1.858	2.214	2.909	3.710	1.343	1.920	1.430	2.045	2.437	3.203
75	1.231	1.760	2.098	2.757	3.521	1.298	1.856	2.211	2.906	3.712	1.341	1.917	1.428	2.042	2.433	3.197
76	1.230	1.759	2.096	2.755	3.519	1.297	1.854	2.209	2.904	3.709	1.339	1.915	1.426	2.039	2.429	3.192
77	1.230	1.758	2.095	2.754	3.517	1.296	1.853	2.207	2.901	3.706	1.336	1.913	1.423	2.035	2.425	3.187
78	1.229	1.758	2.094	2.752	3.516	1.295	1.851	2.206	2.898	3.702	1.335	1.911	1.421	2.032	2.421	3.182
79	1.229	1.757	2.093	2.751	3.514	1.293	1.849	2.204	2.896	3.699	1.333	1.909	1.419	2.029	2.418	3.177
80	1.228	1.756	2.092	2.749	3.512	1.292	1.848	2.202	2.894	3.696	1.334	1.907	1.417	2.020	2.414	3.173
81	1.227	1.755	2.091	2.748	3.510	1.291	1.846	2.200	2.891	3.693	1.332	1.905	1.415	2.023	2.411	3.168
82	1.227	1.754	2.090	2.747	3.509	1.290	1.845	2.198	2.889	3.690	1.331	1.903	1.413	2.020	2.407	3.163
83	1.226	1.753	2.089	2.746	3.507	1.289	1.843	2.196	2.887	3.687	1.329	1.901	1.411	2.017	2.404	3.159
84	1.226	1.753	2.088	2.744	3.506	1.288	1.842	2.195	2.884	3.684	1.328	1.899	1.409	2.014	2.400	3.155
85	1.225	1.752	2.087	2.743	3.504	1.287	1.841	2.193	2.882	3.682	1.327	1.897	1.407	2.012	2.397	3.150
86	1.225	1.751	2.086	2.742	3.503	1.286	1.839	2.191	2.880	3.679	1.326	1.896	1.405	2.009	2.394	3.146
87	1.224	1.750	2.086	2.741	3.501	1.285	1.838	2.190	2.878	3.676	1.324	1.894	1.403	2.007	2.391	3.142
88	1.224	1.749	2.085	2.740	3.500	1.284	1.837	2.188	2.876	3.674	1.323	1.892	1.402	2.004	2.388	3.138
89	1.223	1.749	2.084	2.738	3.498	1.284	1.835	2.187	2.874	3.671	1.322	1.890	1.400	2.001	2.385	3.134
90	1.223	1.748	2.083	2.737	3.497	1.283	1.834	2.185	2.872	3.669	1.321	1.889	1.398	1.999	2.382	3.130
91	1.222	1.747	2.082	2.736	3.495	1.282	1.833	2.184	2.870	3.666	1.320	1.887	1.396	1.997	2.379	3.127
92	1.222	1.747	2.081	2.735	3.494	1.281	1.832	2.182	2.868	3.664	1.319	1.886	1.395	1.994	2.376	3.123
93	1.221	1.746	2.081	2.734	3.493	1.280	1.830	2.181	2.866	3.661	1.318	1.884	1.393	1.992	2.373	3.119

TABLE 2.1

TOLERANCE LIMITS

105

94	1.221	1.745	2.080	2.733	3.401	1.279	1.829	2.180	2.864	3.659	1.317	1.882	2.243	2.943	3.766	1.392	1.990	2.371	3.116	3.080
95	1.220	1.745	2.079	2.732	3.400	1.278	1.828	2.178	2.863	3.657	1.315	1.881	2.241	2.942	3.765	1.390	1.987	2.368	3.112	3.076
96	1.220	1.744	2.078	2.731	3.400	1.278	1.827	2.177	2.861	3.654	1.314	1.880	2.240	2.943	3.760	1.386	1.985	2.360	3.109	3.071
97	1.219	1.743	2.077	2.730	3.400	1.277	1.826	2.175	2.859	3.652	1.312	1.879	2.238	2.941	3.757	1.387	1.983	2.363	3.105	3.067
98	1.219	1.743	2.077	2.729	3.400	1.276	1.825	2.174	2.857	3.650	1.312	1.877	2.236	2.939	3.754	1.385	1.981	2.360	3.102	3.063
99	1.219	1.742	2.076	2.728	3.400	1.275	1.824	2.173	2.856	3.648	1.311	1.875	2.234	2.938	3.751	1.384	1.979	2.358	3.099	3.058
100	1.218	1.742	2.075	2.727	3.400	1.275	1.823	2.172	2.854	3.646	1.311	1.874	2.233	2.934	3.748	1.383	1.977	2.355	3.090	3.054
101	1.218	1.741	2.075	2.726	3.400	1.274	1.821	2.170	2.852	3.644	1.310	1.872	2.231	2.932	3.746	1.381	1.975	2.353	3.092	3.050
102	1.217	1.741	2.074	2.726	3.400	1.273	1.820	2.169	2.851	3.642	1.309	1.871	2.230	2.930	3.743	1.380	1.973	2.351	3.089	3.046
104	1.217	1.739	2.073	2.724	3.400	1.272	1.818	2.167	2.848	3.638	1.307	1.869	2.227	2.926	3.738	1.377	1.969	2.346	3.083	3.039
106	1.216	1.738	2.071	2.722	3.400	1.270	1.816	2.164	2.845	3.634	1.305	1.866	2.224	2.923	3.733	1.374	1.965	2.342	3.077	3.031
108	1.215	1.737	2.070	2.721	3.400	1.269	1.815	2.162	2.842	3.630	1.302	1.861	2.221	2.918	3.728	1.372	1.962	2.337	3.072	3.024
110	1.214	1.736	2.069	2.719	3.400	1.268	1.813	2.160	2.839	3.626	1.302	1.861	2.218	2.915	3.723	1.369	1.958	2.333	3.068	3.017
112	1.211	1.735	2.068	2.717	3.400	1.267	1.811	2.158	2.836	3.623	1.300	1.859	2.215	2.911	3.719	1.367	1.955	2.329	3.061	3.010
114	1.212	1.734	2.067	2.716	3.400	1.265	1.809	2.156	2.833	3.619	1.299	1.857	2.212	2.908	3.714	1.365	1.951	2.325	3.056	3.004
116	1.212	1.733	2.065	2.714	3.400	1.264	1.808	2.154	2.831	3.616	1.297	1.855	2.210	2.904	3.710	1.363	1.948	2.321	3.051	3.001
118	1.212	1.733	2.064	2.713	3.400	1.263	1.806	2.152	2.828	3.613	1.296	1.852	2.207	2.901	3.706	1.360	1.945	2.318	3.040	3.001
120	1.211	1.732	2.063	2.712	3.400	1.262	1.804	2.150	2.826	3.610	1.294	1.850	2.205	2.898	3.702	1.358	1.942	2.314	3.031	3.001
122	1.210	1.731	2.062	2.710	3.400	1.261	1.803	2.148	2.823	3.607	1.293	1.848	2.203	2.895	3.698	1.356	1.939	2.311	3.037	3.001
124	1.210	1.730	2.061	2.709	3.400	1.260	1.801	2.147	2.821	3.604	1.291	1.847	2.200	2.892	3.694	1.354	1.936	2.307	3.032	3.001
126	1.209	1.729	2.060	2.708	3.400	1.259	1.800	2.145	2.819	3.601	1.290	1.845	2.198	2.889	3.690	1.352	1.934	2.304	3.028	3.001
128	1.209	1.728	2.060	2.707	3.400	1.258	1.799	2.143	2.816	3.598	1.289	1.843	2.196	2.886	3.686	1.350	1.931	2.301	3.024	3.001
130	1.208	1.728	2.059	2.705	3.400	1.257	1.797	2.141	2.814	3.595	1.288	1.841	2.194	2.883	3.683	1.349	1.928	2.298	3.019	3.001
132	1.208	1.727	2.058	2.704	3.400	1.256	1.796	2.140	2.812	3.592	1.288	1.839	2.192	2.880	3.679	1.347	1.926	2.295	3.015	3.001
134	1.207	1.726	2.057	2.703	3.400	1.255	1.795	2.138	2.810	3.590	1.285	1.838	2.190	2.878	3.676	1.345	1.923	2.292	3.012	3.001
136	1.207	1.725	2.056	2.702	3.400	1.254	1.793	2.137	2.808	3.587	1.284	1.836	2.188	2.875	3.673	1.343	1.921	2.289	3.008	3.001
138	1.206	1.725	2.055	2.701	3.400	1.253	1.792	2.135	2.806	3.585	1.283	1.834	2.186	2.873	3.669	1.342	1.918	2.286	3.004	3.001
140	1.206	1.724	2.054	2.700	3.400	1.252	1.791	2.134	2.804	3.582	1.282	1.833	2.184	2.870	3.666	1.340	1.916	2.283	3.000	3.001
142	1.205	1.723	2.054	2.699	3.400	1.252	1.790	2.132	2.802	3.580	1.281	1.831	2.182	2.868	3.663	1.338	1.914	2.280	2.997	3.001
144	1.205	1.723	2.053	2.698	3.400	1.251	1.788	2.131	2.801	3.578	1.280	1.830	2.180	2.865	3.660	1.337	1.912	2.278	2.993	3.001
146	1.204	1.722	2.052	2.697	3.400	1.250	1.787	2.130	2.799	3.575	1.279	1.828	2.178	2.863	3.657	1.335	1.909	2.275	2.990	3.001
148	1.204	1.722	2.051	2.696	3.400	1.249	1.786	2.129	2.797	3.573	1.278	1.827	2.177	2.861	3.654	1.334	1.907	2.273	2.987	3.001
150	1.204	1.721	2.051	2.695	3.400	1.248	1.785	2.127	2.795	3.571	1.277	1.825	2.175	2.859	3.652	1.332	1.905	2.270	2.983	3.001
152	1.203	1.720	2.050	2.694	3.400	1.248	1.784	2.126	2.794	3.569	1.276	1.824	2.173	2.858	3.649	1.331	1.903	2.268	2.980	3.001
154	1.203	1.720	2.049	2.693	3.400	1.247	1.783	2.125	2.792	3.567	1.275	1.823	2.172	2.854	3.646	1.330	1.901	2.265	2.977	3.001
156	1.202	1.719	2.049	2.692	3.400	1.246	1.782	2.123	2.791	3.565	1.274	1.821	2.170	2.852	3.644	1.328	1.899	2.263	2.974	3.001
158	1.202	1.719	2.048	2.691	3.400	1.246	1.781	2.122	2.789	3.563	1.273	1.820	2.169	2.850	3.641	1.327	1.897	2.261	2.971	3.001

TABLE 2.1.—(Continued)

$\frac{P}{N}$	$\gamma = 0.75$					$\gamma = 0.90$					$\gamma = 0.95$					$\gamma = 0.99$				
	0.75	0.90	0.95	0.99	0.999	0.75	0.90	0.95	0.99	0.999	0.75	0.90	0.95	0.99	0.999	0.75	0.90	0.95	0.99	0.999
160	1.202	1.718	2.047	2.691	3.437	1.245	1.783	2.121	2.787	3.561	1.272	1.819	2.167	2.848	3.638	1.326	1.896	2.259	2.968	3.792
162	1.201	1.718	2.047	2.690	3.436	1.244	1.779	2.120	2.786	3.559	1.271	1.818	2.166	2.846	3.636	1.324	1.894	2.256	2.965	3.788
164	1.201	1.717	2.046	2.689	3.435	1.244	1.778	2.119	2.785	3.557	1.270	1.816	2.164	2.844	3.634	1.323	1.892	2.254	2.963	3.785
166	1.201	1.717	2.045	2.688	3.434	1.243	1.777	2.118	2.783	3.555	1.269	1.815	2.163	2.843	3.631	1.322	1.890	2.252	2.960	3.781
168	1.200	1.716	2.045	2.687	3.433	1.242	1.776	2.117	2.782	3.553	1.268	1.814	2.162	2.841	3.629	1.321	1.888	2.250	2.957	3.778
170	1.200	1.716	2.044	2.687	3.432	1.242	1.775	2.116	2.780	3.552	1.268	1.813	2.160	2.839	3.627	1.320	1.887	2.248	2.955	3.774
172	1.199	1.715	2.044	2.686	3.431	1.241	1.775	2.115	2.779	3.550	1.267	1.812	2.159	2.837	3.624	1.318	1.885	2.246	2.952	3.771
174	1.199	1.715	2.043	2.685	3.430	1.240	1.774	2.114	2.778	3.548	1.266	1.811	2.158	2.835	3.622	1.317	1.884	2.244	2.950	3.768
176	1.199	1.714	2.043	2.684	3.429	1.240	1.773	2.113	2.776	3.547	1.266	1.810	2.156	2.834	3.620	1.316	1.882	2.243	2.947	3.765
178	1.199	1.714	2.042	2.684	3.428	1.239	1.772	2.112	2.775	3.545	1.265	1.809	2.155	2.832	3.618	1.315	1.880	2.241	2.945	3.762
180	1.198	1.713	2.042	2.683	3.427	1.239	1.771	2.111	2.774	3.543	1.264	1.808	2.154	2.831	3.616	1.314	1.879	2.239	2.942	3.759
185	1.197	1.712	2.040	2.681	3.425	1.237	1.769	2.108	2.771	3.539	1.262	1.805	2.151	2.827	3.611	1.311	1.875	2.234	2.937	3.751
190	1.197	1.711	2.039	2.680	3.423	1.235	1.767	2.106	2.768	3.536	1.261	1.803	2.148	2.823	3.606	1.309	1.872	2.230	2.931	3.744
195	1.196	1.710	2.038	2.678	3.421	1.235	1.766	2.104	2.765	3.532	1.259	1.800	2.145	2.819	3.601	1.307	1.868	2.228	2.926	3.738
200	1.195	1.709	2.037	2.677	3.419	1.234	1.764	2.102	2.762	3.529	1.258	1.798	2.143	2.816	3.597	1.304	1.863	2.222	2.921	3.731
205	1.195	1.708	2.036	2.675	3.418	1.233	1.762	2.100	2.760	3.526	1.256	1.796	2.140	2.812	3.593	1.302	1.862	2.219	2.916	3.725
210	1.194	1.708	2.035	2.674	3.415	1.231	1.761	2.098	2.757	3.522	1.255	1.794	2.138	2.809	3.589	1.300	1.859	2.215	2.911	3.719
215	1.194	1.707	2.034	2.673	3.414	1.230	1.759	2.096	2.755	3.519	1.253	1.792	2.133	2.806	3.585	1.298	1.856	2.212	2.907	3.713
220	1.193	1.706	2.033	2.671	3.413	1.229	1.758	2.095	2.753	3.516	1.252	1.790	2.133	2.803	3.581	1.296	1.854	2.209	2.903	3.708
225	1.192	1.705	2.032	2.670	3.411	1.228	1.756	2.093	2.750	3.514	1.251	1.788	2.131	2.800	3.577	1.294	1.851	2.205	2.898	3.703
230	1.192	1.704	2.031	2.669	3.409	1.227	1.755	2.091	2.748	3.511	1.249	1.787	2.129	2.798	3.574	1.293	1.848	2.202	2.894	3.697
235	1.191	1.704	2.030	2.668	3.408	1.226	1.754	2.090	2.746	3.508	1.248	1.785	2.127	2.795	3.571	1.291	1.846	2.199	2.890	3.692
240	1.191	1.703	2.029	2.667	3.407	1.226	1.752	2.088	2.744	3.506	1.247	1.783	2.125	2.792	3.567	1.289	1.843	2.197	2.887	3.688
245	1.190	1.702	2.028	2.666	3.405	1.225	1.751	2.087	2.742	3.503	1.246	1.782	2.123	2.790	3.564	1.288	1.841	2.194	2.883	3.683
250	1.190	1.702	2.028	2.665	3.404	1.224	1.750	2.085	2.740	3.501	1.245	1.780	2.121	2.788	3.561	1.286	1.839	2.191	2.880	3.678
255	1.190	1.701	2.027	2.664	3.403	1.223	1.749	2.084	2.739	3.499	1.244	1.779	2.119	2.785	3.558	1.284	1.837	2.189	2.876	3.674
260	1.189	1.700	2.026	2.663	3.401	1.222	1.748	2.083	2.737	3.496	1.243	1.777	2.118	2.783	3.555	1.283	1.835	2.186	2.873	3.670
265	1.189	1.700	2.025	2.662	3.400	1.222	1.747	2.081	2.735	3.494	1.242	1.776	2.116	2.781	3.552	1.282	1.833	2.184	2.870	3.666
270	1.188	1.699	2.025	2.661	3.399	1.221	1.746	2.080	2.734	3.492	1.241	1.774	2.114	2.779	3.550	1.280	1.831	2.181	2.867	3.662

TABLE 2.1

TOLERANCE LIMITS

107

275	1.188	1.699	2.024	2.669	3.398	1.220	1.745	2.079	2.732	3.490	1.240	1.773	2.113	2.777	3.547	1.279	1.829	2.179	2.864	3.658
280	1.188	1.698	2.023	2.659	3.397	1.219	1.744	2.078	2.730	3.488	1.239	1.772	2.111	2.775	3.544	1.278	1.827	2.177	2.861	3.655
285	1.187	1.698	2.023	2.658	3.396	1.219	1.743	2.076	2.729	3.486	1.238	1.771	2.110	2.773	3.542	1.276	1.825	2.175	2.858	3.651
290	1.187	1.697	2.022	2.657	3.395	1.218	1.742	2.075	2.727	3.484	1.237	1.769	2.108	2.771	3.540	1.275	1.823	2.173	2.855	3.647
295	1.186	1.697	2.022	2.657	3.394	1.217	1.741	2.074	2.726	3.482	1.236	1.768	2.107	2.769	3.537	1.274	1.822	2.172	2.853	3.644
300	1.186	1.696	2.021	2.656	3.393	1.217	1.740	2.073	2.725	3.481	1.236	1.767	2.106	2.767	3.535	1.273	1.820	2.169	2.850	3.641
310	1.185	1.695	2.020	2.655	3.391	1.216	1.738	2.071	2.722	3.477	1.234	1.765	2.103	2.764	3.531	1.271	1.817	2.168	2.845	3.638
320	1.185	1.694	2.019	2.653	3.389	1.215	1.737	2.069	2.719	3.474	1.233	1.763	2.100	2.760	3.526	1.268	1.814	2.161	2.840	3.634
330	1.184	1.693	2.018	2.652	3.388	1.213	1.735	2.067	2.717	3.471	1.231	1.761	2.098	2.757	3.522	1.266	1.811	2.158	2.836	3.623
340	1.184	1.693	2.017	2.651	3.386	1.212	1.734	2.065	2.715	3.469	1.230	1.759	2.096	2.754	3.519	1.265	1.808	2.154	2.831	3.617
350	1.183	1.692	2.016	2.649	3.384	1.211	1.732	2.064	2.713	3.465	1.229	1.757	2.094	2.752	3.515	1.263	1.805	2.151	2.827	3.612
360	1.183	1.691	2.015	2.648	3.383	1.210	1.731	2.062	2.710	3.463	1.228	1.755	2.092	2.749	3.512	1.261	1.803	2.148	2.823	3.607
370	1.182	1.690	2.014	2.647	3.382	1.210	1.730	2.061	2.708	3.460	1.227	1.754	2.090	2.746	3.508	1.259	1.801	2.146	2.820	3.602
380	1.182	1.690	2.013	2.646	3.380	1.209	1.728	2.059	2.707	3.458	1.225	1.752	2.088	2.744	3.505	1.258	1.798	2.143	2.818	3.598
390	1.181	1.689	2.013	2.645	3.379	1.208	1.727	2.058	2.705	3.455	1.224	1.751	2.086	2.742	3.502	1.255	1.796	2.140	2.813	3.593
400	1.181	1.688	2.012	2.644	3.378	1.207	1.726	2.057	2.703	3.453	1.223	1.749	2.084	2.739	3.499	1.255	1.794	2.138	2.809	3.589
425	1.180	1.687	2.010	2.642	3.375	1.205	1.723	2.054	2.699	3.448	1.221	1.746	2.080	2.734	3.492	1.251	1.789	2.132	2.802	3.579
450	1.179	1.686	2.009	2.640	3.372	1.204	1.721	2.051	2.695	3.443	1.219	1.743	2.077	2.729	3.486	1.248	1.785	2.127	2.795	3.570
475	1.178	1.685	2.007	2.638	3.370	1.202	1.719	2.048	2.692	3.438	1.217	1.740	2.073	2.725	3.481	1.245	1.781	2.122	2.788	3.562
500	1.177	1.683	2.000	2.636	3.368	1.201	1.717	2.045	2.689	3.434	1.215	1.737	2.070	2.721	3.475	1.243	1.777	2.117	2.783	3.555
525	1.177	1.682	2.003	2.635	3.366	1.199	1.715	2.043	2.680	3.431	1.213	1.735	2.067	2.717	3.471	1.240	1.773	2.113	2.777	3.548
550	1.176	1.681	2.004	2.633	3.364	1.198	1.713	2.041	2.683	3.427	1.212	1.733	2.065	2.713	3.466	1.238	1.770	2.108	2.772	3.541
575	1.175	1.681	2.003	2.632	3.362	1.197	1.712	2.039	2.680	3.424	1.210	1.731	2.062	2.710	3.462	1.236	1.767	2.105	2.767	3.535
600	1.175	1.680	2.002	2.631	3.360	1.196	1.710	2.038	2.678	3.421	1.209	1.729	2.060	2.707	3.459	1.234	1.764	2.102	2.763	3.530
625	1.174	1.679	2.001	2.629	3.359	1.195	1.709	2.036	2.676	3.418	1.208	1.727	2.058	2.704	3.455	1.232	1.762	2.099	2.759	3.525
650	1.174	1.678	2.000	2.628	3.357	1.194	1.707	2.034	2.674	3.416	1.207	1.725	2.056	2.702	3.451	1.230	1.759	2.096	2.755	3.520
675	1.173	1.676	1.999	2.627	3.355	1.193	1.706	2.033	2.672	3.413	1.206	1.724	2.054	2.699	3.448	1.229	1.757	2.094	2.752	3.515
700	1.173	1.677	1.998	2.626	3.355	1.192	1.705	2.032	2.670	3.411	1.204	1.722	2.052	2.697	3.445	1.227	1.755	2.091	2.748	3.511
725	1.172	1.676	1.998	2.625	3.354	1.192	1.704	2.030	2.668	3.408	1.203	1.721	2.050	2.694	3.442	1.226	1.753	2.089	2.745	3.507
750	1.172	1.676	1.997	2.624	3.352	1.191	1.703	2.029	2.667	3.406	1.202	1.719	2.049	2.692	3.439	1.225	1.751	2.086	2.742	3.503
780	1.171	1.675	1.996	2.623	3.350	1.189	1.701	2.027	2.665	3.402	1.201	1.717	2.046	2.688	3.434	1.222	1.747	2.082	2.736	3.495
800	1.171	1.675	1.994	2.621	3.348	1.188	1.699	2.025	2.661	3.399	1.199	1.714	2.043	2.683	3.430	1.220	1.744	2.078	2.731	3.489
850	1.170	1.673	1.993	2.620	3.347	1.187	1.697	2.023	2.658	3.396	1.198	1.712	2.040	2.682	3.426	1.218	1.741	2.075	2.726	3.483
900	1.169	1.672	1.992	2.619	3.345	1.186	1.696	2.021	2.656	3.393	1.196	1.710	2.038	2.679	3.422	1.216	1.738	2.071	2.722	3.477
950	1.169	1.671	1.992	2.617	3.344	1.185	1.695	2.019	2.654	3.390	1.195	1.709	2.036	2.676	3.418	1.214	1.736	2.068	2.718	3.472
1,000	1.168	1.670	1.991	2.616	3.343	1.184	1.694	2.018	2.653	3.389	1.194	1.708	2.035	2.675	3.417	1.213	1.735	2.067	2.717	3.471
∞	1.167	1.669	1.990	2.615	3.342	1.183	1.693	2.017	2.652	3.388	1.193	1.707	2.034	2.674	3.416	1.212	1.734	2.066	2.716	3.470

TABLE 2.2
COEFFICIENTS TO FACILITATE THE USE OF FORMULA (6) FOR COMPUTING K WHEN N IS
LARGE

Coefficient	Value	$\gamma = 0.75$	$\gamma = 0.90$	$\gamma = 0.95$	$\gamma = 0.99$
Term in $\frac{1}{\sqrt{N}}$	$\frac{x_\gamma}{\sqrt{2}}$	0.4769	0.9062	1.1631	1.6450
Term in $\frac{1}{N}$	$\frac{5x_\gamma^2 + 10}{12}$	1.0229	1.5177	1.9606	3.0883

3. CONSTRUCTION OF THE TABLE

3.1. Formula

The formula for K used in Table 2.1 is*

$$K = r \sqrt{\frac{N}{\chi_\gamma^2}} \quad (13)$$

where N is the number of observations, P is the proportion of the distribution to be included within the tolerance limits, γ is the confidence coefficient, r is a function of $1/\sqrt{N}$ and P defined by

$$\frac{1}{\sqrt{2\pi}} \int_{\frac{1}{\sqrt{N}} - r}^{\frac{1}{\sqrt{N}} + r} e^{-\frac{t^2}{2}} dt = P \quad (14)$$

and χ_γ^2 is defined by

$$P(\chi^2 > \chi_\gamma^2) = \gamma \quad (15)$$

in terms of the chi-square distribution for n degrees of freedom, where

$$n = N - 1. \quad (16)$$

3.2. Basic Network of Points

K was computed directly from formula (13) for all values of n (that is, of $N - 1$) from 1 to 30, for all even values of n from 30 to 60, for values of n from 60 to 200 at intervals of 10, and for values of n from 199 to 999 at intervals of 50. For other values of n , values of K were interpolated into this basic network of points by means of 4-point Lagrangian interpolatory coefficients taken from the table published by the New York Mathematical Tables Project.

3.3. Percentage Points of χ^2

For all values of n from 1 to 30 and for values from 30 to 100 at intervals of 10, the percentage points of χ^2 were obtained from Thomp-

* This formula was developed in the Statistical Research Group by A. Wald and J. Wolfowitz; see their paper cited in Sec. 4.

son's table. Since for even n the probability of exceeding any given value χ^2 is given by the partial sum of a Poisson series, the required values between $n = 30$ and $n = 60$ (except $n = 40$ and $n = 50$) were obtained by inverse interpolation in Molina's table* using Salzer's inverse interpolation coefficients. The percentage points of χ^2 for $n > 100$ were found from a Cornish-Fisher type of expansion applied to the χ^2 distribution.†

3.4. Computation of r

To compute r , Newton's method was applied to the function

$$G(r) = \frac{1}{\sqrt{2\pi}} \int_{\frac{1}{\sqrt{N}} - r}^{\frac{1}{\sqrt{N}} + r} e^{-\frac{t^2}{2}} dt - P = 0 \quad (17)$$

The NYMTP tables of the probability integral are conveniently arranged for this, since the ordinates of the normal curve are tabulated beside the integral, and forward interpolation in both the integral and the ordinate may be expressed simply in terms of the ordinate.

4. REFERENCES

- BOWKER, ALBERT H.: "Computation of Factors for Tolerance Limits on a Normal Distribution When the Sample Is Large," *Annals of Mathematical Statistics*, Vol. 17 (1946), pp. 238-240.
- GOLDBERG, HENRY, and LEVINE, HARRIET: "Approximate Formulas for the Percentage Points and Normalization of t and χ^2 ," *Annals of Mathematical Statistics*, Vol. 17 (1946), pp. 216-225.
- Mathematical Tables Project, Work Projects Administration for the City of New York, Federal Works Agency: *Tables of Probability Functions*, Vol. 2, National Bureau of Standards, Washington, D. C., 1942, 344 + xxi pp.
- : *Tables of Lagrangian Interpolation Coefficients*, Columbia University Press, New York, 1944, 392 + xxxvi pp.
- MOLINA, E. C.: *Poisson's Exponential Binomial Limit*, D. Van Nostrand Company, Inc., New York, 1942, 47 pp.
- PAULSON, EDWARD: "A Note on Tolerance Limits," *Annals of Mathematical Statistics*, Vol. 14 (1943), pp. 90-93.
- ROBBINS, HERBERT: "On Distribution-free Tolerance Limits in Random Sampling," *Annals of Mathematical Statistics*, Vol. 15 (1944), pp. 214-216.
- SALZER, H. E.: "Table of Coefficients for Inverse Interpolation with Advancing Differences," *Journal of Mathematics and Physics*, Vol. 23 (1944), pp. 75-102.
- SCHIEFFÉ, H., and TUKEY, J. W.: "A Formula for Sample Sizes for Population Tolerance Limits," *Annals of Mathematical Statistics*, Vol. 15 (1944), p. 217.

* In Molina's notation

$$P\left(\frac{n}{2}, \frac{\chi^2}{2}\right) = 1 - \gamma$$

† The application of the Cornish-Fisher method to the χ^2 distribution was carried out in the Statistical Research Group by Henry Goldberg and Harriet Levine; see their paper cited in Sec. 4.

- SHEWHART, WALTER A., with the editorial assistance of DEMING, W. EDWARDS: *Statistical Method from the Viewpoint of Quality Control*, Graduate School, U.S. Department of Agriculture, Washington, D. C., 1939, 155 + ix pp.
- THOMPSON, CATHERINE M.: "Table of Percentage Points of the χ^2 Distribution," *Biometrika*, Vol. 32 (1941), pp. 188-189.
- WALD, ABRAHAM: "Setting of Tolerance Limits When the Sample Is Large," *Annals of Mathematical Statistics*, Vol. 13 (1942), pp. 389-399.
- : "An Extension of Wilks' Method of Setting Tolerance Limits," *Annals of Mathematical Statistics*, Vol. 14 (1943), pp. 45-55.
- , and WOLFOWITZ, J.: "Tolerance Limits for a Normal Distribution," *Annals of Mathematical Statistics*, Vol. 17 (1946), pp. 208-215.
- WILKS, S. S.: "Determination of Sample Sizes for Setting Tolerance Limits," *Annals of Mathematical Statistics*, Vol. 12 (1941), pp. 91-96.
- : "Statistical Prediction with Special Reference to the Problem of Tolerance Limits," *Annals of Mathematical Statistics*, Vol. 13 (1942), pp. 400-409.

CHAPTER 3

MULTIVARIATE QUALITY CONTROL, ILLUSTRATED BY THE AIR TESTING OF SAMPLE BOMBSIGHTS

	Page
1. Introduction	113
1.1 Type of Problem	113
1.2 Problems of Air-testing Bombsights.	116
2. Proposed Sampling Plan.	119
2.1 Selection of Sample Sights and Arrangement of Bombing.	119
2.2 Control Charts.	122
2.2.1 General Plan	122
2.2.2 Control Chart for Mean Range	123
2.2.3 Control Chart for Mean Deflection.	127
2.2.4 Control Chart for Range Variance.	127
2.2.5 Control Chart for Deflection Variance	131
2.2.6 Control Charts Combining Range with Deflection	131
2.2.7 Illustration of the Use of Control Charts.	135
2.3 Action When Results Are Bad	137
2.4 Experimentation	140
3. Formulas and Considerations Affecting Revisions of the Plan.	142
3.1 General Considerations	142
3.1.1 Occasions for Revision	142
3.1.2 Numbers of Sights, Flights, and Bombs.	143
3.1.3 Revision Based on New Experience	144
3.1.4 Assumptions Involved	146
3.2 Means.	147
3.2.1 Control Limits for Means.	147
3.2.2 Asymmetry of Control Limits and Bias in Base Period	149
3.2.3 Yardsticks for Differences of Means	150
3.3 Variances	151
3.3.1 Control Limits for Variances	151
3.3.2 Yardsticks for Variances	152
3.4 Comprehensive Measures	152
3.4.1 Control Limits for the T 's.	152
3.4.2 Yardsticks for the T 's	156
4. Background and Reasons for the Plan.	156
4.1 Objectives of Sampling Inspection.	156
4.2 Reasons for Random Selection and for Lot Size 20	158
4.3 Relation to Experimental Design	159
4.4 Efficient Formulas for Utilizing Results	160
4.5 Exact Probabilities	163
4.6 Reasons for the T Method of Combining Range and Deflection Errors.	164
5. Statistical Analysis of Certain Test Bombings	168
5.1 Summary of the Data.	168
5.2 Analysis of the Data	170
5.3 Ratings of Equipment and Personnel by Test Bombing	176
6. References.	183

FIGURES

PAGE

3.1	Control Chart for Mean Range \bar{r} .	124
3.2	Control Chart for Mean Deflection \bar{d} .	126
3.3	Control Chart for Range Variance s_r^2 .	128
3.4	Control Chart for Deflection Variance s_d^2 .	130
3.5	Control Chart for Error in Mean Point of Impact T_M .	132
3.6	Control Chart for Dispersion about Mean Point of Impact T_D .	134
3.7	Control Chart for Over-all Error T_O .	136
3.8	Over-all Measure of Error T_O^2 Applied to Sample Data.	178
3.9	Errors in MPI in Sample, as Measured by T_M^2 .	179
3.10	Dispersion Measure T_D^2 Applied to Sample Data.	180

TABLES

3.1	Summary of Bombing Errors in 65 Flights (260 bombs)	169
3.2	Distribution of Flights by Personnel and Equipment.	170
3.3	Effect of Equipment on Over-all Accuracy of Bombing.	181
3.4	Variation of Over-all Accuracy with Personnel.	182

This chapter was prepared by
Harold Hotelling, University of North Carolina

CHAPTER 3

MULTIVARIATE QUALITY CONTROL, ILLUSTRATED BY THE AIR TESTING OF SAMPLE BOMBSIGHTS

1. INTRODUCTION

1.1. Type of Problem

Systematic plans of sampling for acceptance inspection or quality control are for the most part based on simple features of the individual articles inspected. Usually each article is classified merely as defective or nondefective. In a minority of cases there is a finer classification involving measurement of continuous variates. In the inspection of simple articles, including component parts of complicated assemblies, inspection by attributes is considered appropriate; but in the inspection of complicated assemblies, especially when inspection is costly, measurements are apt to be advantageous.* Furthermore, the performance of complicated assemblies is usually a function of several different variables. When several quality characteristics are measured, there arises a problem of combining the several measurements on each article into a single measure ("score" or "index") of the over-all performance of the article.†

In the absence of a formally defined procedure, methods of a more or less subjective character for combining the different measurements to form a judgment of degree of acceptability are bound to develop. The simplest such method is to apply customary practices to each variate separately and to reject whenever the usual rules applied to any one variate alone lead to a verdict of rejection. This procedure, however, has the effect of changing drastically the probabilities, both of accepting what is bad and of rejecting what is good. For example, if a sampling scheme is designed to give a probability of 0.05 of rejecting a lot of a certain quality on the basis of measurements of one variate, and if this scheme is applied to each of two variates measured on the same articles, then if the two variates are independently distributed, rejection on the basis of one or the other variate will take place in 9.75 per cent of submitted lots of the given quality instead of 5 per cent as originally contemplated. The discrepancy between the actual and the intended probabilities of rejection will increase rapidly with the number of independent variates when such a rule is followed.

* For a further discussion of this point, see Chap. 1, Sec. 1.

† For a further discussion of this point, see Chap. 1, Sec. 10.1.

An alternative rule, erring in the opposite direction, would be to accept any lot for which the univariate scheme applied to *any one* of the variates calls for acceptance. Thus rejection would require that *all* the variates take such values as to call for rejection. For two independent variates, a probability of rejection intended to be 0.90 would actually in such a case be only 0.81.

These probabilities can be adjusted so as to become equal to 0.05, or such level as is chosen, by altering the acceptance level for each variate separately. However, this brings in additional difficulties. The variates may not be mutually independent, and then calculations such as the foregoing must be altered to take into account the multivariate distribution. Furthermore, it will often not be known whether they are independent or not; or if they are mutually dependent, the character of the dependence may be known only imperfectly. Thus the correlation coefficient may have to be estimated from a preliminary sample of size so small as to leave its exact value somewhat uncertain. Any acceptance probabilities based on such a correlation coefficient will then likewise be uncertain.

Rules such as those suggested above have another defect. An article close to the margin of acceptability with respect to one variate may well be marked for acceptance or rejection on the basis of the other variates involved. Unusual excellence in one respect may often atone for a slight departure in another way from what would otherwise be considered satisfactory. A formula is then needed for combining the measures in the several dimensions into a single measure of excellence, or of adherence to specifications or to a desired ideally uniform set of dimensions. Such a formula should give a measure of departure from the ideal that will increase with a departure in any dimension. It should lend itself to an exact interpretation in terms of probability, taking account of the necessarily limited size of any preliminary sample used to determine the parameters entering into the formula.

Formulas of this type are here developed on the basis of an expression known as the generalized Student ratio T , introduced in 1931 for the testing of hypotheses about the location of the means of multivariate distributions and closely related to the exponent in the multivariate normal distribution.* If errors in two or more dimensions were mutually uncorrelated and of equal variance in the sample representing past experience, the value of T for a new individual would be directly proportional to the distance from the point whose rectangular coordinates represent the ideal to the point representing the actual measurements. Thus, for a bomb dropped on a target, T would in such a case be simply

* See HOTELLING, "The Generalization of Student's Ratio." (For full citations, see Sec. 6.)

the distance of the bomb from the center of the target, expressed in terms of a unit equal to the standard deviation found in the earlier experience. Actually, the variances of range errors in bombing are appreciably less than those of deflection errors.* Consequently, the expression used for T^2 has different coefficients for the two squared terms. In addition, it has a term in the product of range and deflection errors, the small coefficient of which results from a slight correlation between the two kinds of error in the available experience. This T^2 serves as a measure of the deviation of the particular bomb from the center of the target, a measure more accurately interpretable in terms of probability than is the actual distance. By adding the values of T^2 for all the bombs dropped with a particular bombsight, we have a measure useful in judging the accuracy of that bombsight. There are also other ways of combining these T 's to throw light on particular features.

A great advantage of all these T statistics is that, in samples from normal distributions, they have probability distributions that can be determined *exactly*. Many statistics have distributions involving what may be called "nuisance parameters," that is, parameters which are not known exactly from general considerations or basic scientific constants but have to be estimated, with more or less uncertainty, from fallible observations. This is true, for example, of the actual distance of a bomb from a target, whose distribution depends not only on the mean value of such distances but also, and in a complicated way, on the *direction* of the deviation. The parameters specifying the distribution of the direction—which is really irrelevant—are nuisance parameters in the distribution of the actual distance, confusing its interpretation as a measure of accuracy of the bomb. But the T statistics have been constructed in such a way that there are no nuisance parameters involved in their distributions, at least as long as we are dealing with data from a fundamental distribution of the normal form.

It is to be expected that these T statistics will have many applications in sampling inspection and in other fields. In particular, wherever a manufactured article is to be judged, not on the basis of measurement of parts, but on the basis of final performance as measured by several variables, there seems to be room for the utilization of such methods. A case of this kind, which is here considered in detail and for which the methods presented here were originated, is that of air testing sample bombsights. It is presented here as a precedent that will be useful in other situations in which final performance is determined by multiple measurements.

* An error in range is an error in the direction of the airplane's heading at the time of release. An error in deflection is an error in a direction perpendicular to the plane's heading.

The mathematical theory is not given in full in this chapter, but the methods recommended will, it is believed, be fully intelligible on the basis of the material presented here.*

Besides the T distribution, several other innovations are here suggested, both graphic devices and methods of applying to statistical quality control some of the ingenious devices and concepts that R. A. Fisher has introduced into the design of experiments.

1.2. Problems of Air Testing Bombsights

The dropping of bombs from airplanes for the purpose of testing bombsights submitted by manufacturers is a phase of quality control. The art and the literature of quality control, so greatly expanded of late, are to a certain extent applicable to this bombing procedure. Yet test bombing presents several novel features that make the situation very different from those heretofore dealt with in the literature and usual practice of quality control. These peculiar features, which make this no ordinary problem and render the usual methods inadequate and to some extent inappropriate, are the following:

(1) In contrast to the simple articles to which routine mass sampling inspection is usually applied, with at most one or two numbers recorded for each article tested, and often merely a "good" or "bad" verdict, the bombsight is a highly complex instrument with a multiplicity of parts, each of which is subject to various possible defects.

(2) The process of putting together these parts in selective assembly, matching an oversize part with an undersize part to fit in with it, grinding and adjusting when necessary, is a series of jobs requiring great skill, whose results are to be judged by the performance of the finished instrument rather than by measurement of parts. Performance, however, is a complicated thing. If quality is to be measured by performance and expressed by one or a few numbers, caution must be exercised in the choice of these numbers and their interpretation.

(3) Air testing is only one of a series of tests and inspections to which a bombsight and its parts are subjected. It is the final step, and an exceptionally costly one. For elimination of defects the main reliance is properly placed on earlier and cheaper steps. A great deal of careful screening out of defectives has taken place prior to the final stage of air testing, with which alone this chapter is concerned.

(4) The errors of test bombing are not by any means due entirely to defects in the sight. In spite of all attempts at standardization there are bound to be variations in the weather, the altitude from which the bombs are dropped, the bombs themselves, the airplane, the auxiliary equip-

* It is planned to present the mathematical theory in the *Annals of Mathematical Statistics*.

ment, and the personnel engaged in flying, bombing, and observing the results. The variance in the results of the bombing that results from causes having nothing to do with the quality of the bombsight indicates that, while valuable statistical inferences are possible from large numbers of cases, it would be a dubious procedure to take any drastic action on the basis of the four or six bombs usually dropped with a sight, except perhaps in the most extreme cases.

(5) When bombing with a particular sight shows unsatisfactory results, the action ordinarily taken is not the rejection of the sight, but its adjustment or repair.

(6) Whereas the usual sampling inspection for quality control is carried out very cheaply for each single inspection by a workman of moderate skill using some simple instrument, the dropping of a test bomb requires a pilot, a bombardier, an airplane with gasoline and maintenance, an airfield, a target area, stations for observing the point of impact and personnel to man them, and finally, plotting and computations.

The function of air testing is clearly not the elimination of individual bad sights or of bad lots of 10 from which the sights tested are taken. This is done far more efficiently by inspection of parts and by shop testing of the finished bombsight, both by the manufacturer and by the government representatives at the factory, as well as by the shop testing of the sample sent to the government proving ground. The principal functions which air testing is capable of fulfilling appear rather to be the following:

(1) Keeping a running record of quality designed to compare the work of different productive units, and of the same unit at different times.

(2) Detection of irregularities, trends in quality, and deviations from customary levels in the average performance of sights produced over a period.

(3) Exploration of possible types of defects, either in design or in production, not previously recognized.

(4) By experiments carefully designed so as not to conflict with the other purposes of air testing, to obtain judgments on differing models of sights, on auxiliary equipment, on bombing methods, and on personnel in a manner more efficient than separate experiments carried out solely to obtain these judgments.

The high cost and uncertainty of air testing, with the relative accuracy and low cost of shop testing, indicate that only a very small number of bombsights should be air-tested. However, it does appear that some air testing should go on, for reasons outside those usual in sampling inspection and to an extent that cannot be determined by calculation according to customary methods. In the specific, though flexible, plan suggested in Sec. 2, the amount of routine bombing called for is one-twentieth of that under procedures in effect in 1943. The exact proportion suitable

cannot be derived by calculation from the proportion of defects, which could not be ascertained reliably from the record because of the virtual absence of defects serious enough to cause rejection. The fraction suggested represents what is in the author's view a reasonable proportion of bombsights to be tested if the improved statistical methods described herein are utilized. The plan can easily be modified, in accordance with Sec. 3, to fit any other proportion considered appropriate.

In much quality-control work where individual inspection is cheap, inefficient statistical formulas are used frankly and deliberately when they are easy to calculate and to comprehend. The saving in computation represented by using the mean deviation instead of the standard deviation with many small batches may in some circumstances offset the increase of approximately one-eighth in the amount of inspection necessary to get the same accuracy. The range of a sample (that is, the difference between the greatest and least of the values) is often taken as a measure of dispersion when it is felt that the inability of factory employees to understand any more sophisticated measure warrants the cost of the additional observations required to obtain the necessary accuracy.

Considerations of this kind should have no place where the unit cost is as great as that of dropping a bomb. Information acquired at such great expense should not be wasted by the use of inefficient statistical methods of combining the observations. One object of this chapter is to set forth the most appropriate methods of combining the observations of the bomb coordinates and of making inferences from them. Some modifications of the usual kinds of control charts are introduced. Furthermore, the contribution of modern statistical methods to the improvement of accuracy is not limited to formulas for combining the observations after they are made. Certain precautions, such as proper randomization and replication, can be arranged only *before* the observations are made. The application of these principles to air-testing sample bombsights by a plan in accordance with modern principles of experimental design is another leading purpose of this chapter.

Section 2 consists of a specific plan for the selection of sample bombsights, their air testing, the calculations to be made from the results, a series of control charts of new types, and some simple considerations relevant to interpretation of the results and to action.

Since Sec. 2 is easily adaptable to changed conditions and modifications of the plan, formulas are given in Sec. 3 for calculating new control limits and other needed quantities under conditions more general than those of Sec. 2. Provision is here made for changing the number of bombs dropped per flight, the number of flights with each sight, the number of sights to be taken from a lot for air testing, and the base period with which comparison is to be made.

While Secs. 2 and 3 consist principally of simple rules for operating and for amending the sampling plan, with little mathematics or argumentation, Sec. 4 gives the background and reasons for the plan. The chief mathematical discussion has, however, been confined to a technical paper, where the mathematical reader will find a more precise account of some of the new ideas presented here for the first time. These ideas are applicable to a wide range of problems, not only in quality control but also in connection with bombing and firing in general, with mental testing, and with other problems in which two or more normally distributed variates are involved.

Section 5 is an analysis of the results of dropping 260 ore-filled bombs. Measures of dispersion obtained from these bombs are substituted into the formulas of Sec. 3 to obtain the control limits specified in the plan of Sec. 2, together with coefficients for combining range and deflection errors and other needed quantities. For any sampling plan, a base period is needed to get the plan started, and this is provided by the material analyzed in Sec. 5. This section also contains as by-products a specimen rating of equipment and personnel involved in that bombing, essentially to show how such ratings can be made, and a new simplified technique of analysis of variance with unequal class frequencies developed for the purpose of making these ratings.

This chapter includes control charts having several novel features, which it is believed will also be found useful in other control-chart work. One is the choice of the functions combining different *measures of* accuracy, here range and deflection errors, to be plotted. These functions are invariant under transformations of coordinates and hence have probability distributions capable of exact determination. Another feature of the control charts here presented is the provision of *yardsticks*, for visual comparison of different plotted values, with a definite probability interpretation.

In fixing the control limits corresponding to specified probabilities, account is here taken of the limited number and consequent sampling fluctuations of the observations in the base period used for comparison. It is to be feared that in many control charts heretofore in use there has been an unconscious distortion of the probabilities because of neglect of this consideration, with a bias uniformly in the direction of exaggerating the significance of moderately large deviations from norms. Use of formulas such as those of Sec. 3 in industrial quality control should correct this error.

2. PROPOSED SAMPLING PLAN

2.1. Selection of Sample Sights and Arrangement of Bombing

(1) Whenever a new factory goes into production, each of the first 40 bombsights produced and passing the usual shop tests of the govern-

ment inspectors, both at the factory and at the proving ground, is to be tested. If all these are found satisfactory, the remainder of the plan is to be applied to subsequent production, subject to withdrawal with reversion to the status of a new factory if later a series of unacceptable sights is offered. (Since the last contingency has not hitherto occurred, accurate formulation of a definite rule for such reversion must await the accumulation of this undesirable kind of experience.)

(2) At each factory that has been approved after the first 40 bomb-sights, the sights of each model are to be numbered consecutively in the order of manufacture in each of two series. One series, designated *A*, shall consist of those sights approved without unusual delay by the government inspector at the factory on first delivery by the manufacturer. The other series, designated *B*, shall consist of those sights first rejected by the government inspector and later approved after defects have been remedied, together with any other approved sights whose approval has for any reason been delayed. To each sight are to be affixed both the usual serial number representing original order of manufacture and the letter *A* or *B*, with the number within the *A* or *B* series. The subsequent procedures are to be applied separately to the *A* and *B* series for each factory and for each model.

(3) Each series is to be divided into successive lots of 20, strictly in the order of original manufacture.

(4) From each lot of 20, two sights are to be selected by an objective chance procedure and sent to the proving ground. No element of personal judgment or of rating on inspection should enter into this selection, which may be made in the following manner: the procurement authorities will send to the chief inspector at the factory a series of opaque sealed envelopes marked on the outside with the first and last serial numbers of the successive batches. An envelope is to be opened only after the inspection at the factory of all the sights in a batch has been completed and report made. Within the envelope will be found two numbers between 1 and 20, inclusive, prepared on a strictly chance basis, with equal probabilities for all twenty numbers. This must be done through actual utilization of a chance mechanism or of a table of random numbers,* without human discretion other than in the selection of the mechanism. One obvious procedure would be to mark twenty playing cards with the numbers 1 to 20, and after thoroughly shuffling to draw out two of them at random.

(5) The remaining 18 sights of each lot are not to be held at the factory until completion of the air testing of the sample but should be

* For example, FISHER and YATES, *Statistical Tables*, Table XXXIII; KENDALL and SMITH, *Random Sampling Numbers*; TIPPETT, *Random Sampling Numbers*.

sent directly to service, subject to later recall or repair in the unlikely event that the sample is found seriously defective.

(6) Upon arrival at the proving ground, the sample sights are all to be shop-tested and adjusted as at present, with such further types of shop test as may be developed.

(7) By an objective random procedure like that described in Paragraph (1) above, lots are to be selected for the air testing of the two sights representing the lot at the proving ground. It is suggested that one-fortieth of the lots produced by each manufacturer be selected by chance. (It is likely that this proportion should be reduced as the improved methods of shop testing prove their value.)

(8) Each of the two sights representing each of the lots selected in accordance with Paragraph (7) is to be taken up in an airplane twice to be used for dropping bombs.

(9) The routine flight testing is to be arranged in periods, each consisting of four consecutive days, or four days as nearly consecutive as possible even though there may be breaks on account of Sundays or special circumstances. The number of test flights to be made per day should first be determined and will here be denoted by k . This same number of flights k should be made on each day of the 4-day period, though it is not essential that k should be the same for different periods.

(10) The sights to be tested in a 4-day period are to be the two sample sights from each of k lots. Each sight is to be tested on two different days of the period, and each lot is to be represented on all four days. Subject to these conditions, the assignment of the particular sight of a lot to be tested on a specific day is to be decided by objective chance, for example, by flipping a coin. The k lots represented may be from the same or different factories. They may be of different models and may be of A or B series or both.

(11) Exactly four bombs are to be dropped on each flight. Range and deflection errors are to be measured with respect to the heading of the airplane at the time the particular bomb was dropped.

(12) The numerical values for control limits and yardsticks given in this section are to be used only if the directions in the preceding eleven paragraphs are carried out exactly. If it is decided to revise the plan by dropping a different number of bombs on each flight, or by measuring range and deflection with respect to the true course instead of the heading, the numerical values will need to be amended in accordance with the formulas of Sec. 3. The number of bombs dropped per flight will be denoted by N , with the understanding in this section that $N = 4$. No change should be made except as part of an explicit revision of the plan.

(13) All measures of quality based on the bombing results should be algebraic functions of the coordinates of the bombs with respect to the

target, taken with their proper algebraic signs. Absolute values and mean deviations are not algebraic functions and should not be employed in this connection. Use of criteria based on mean deviations requires more bombing to procure comparable accuracy than the formulas used herein. Furthermore, in contrast to the T measures here recommended, no combination of mean deviations has an exactly known distribution.

2.2. Control Charts

2.2.1. General Plan.—Seven control charts, illustrated by Figs. 3.1 to 3.7,* are to be kept for each factory and model and for the A and B series. On these charts certain indicators of quality of successive lots are plotted, strictly in the order of production. Entries on these charts should be made daily as soon as the data become available. The charts should be posted conspicuously at the proving ground where they will be seen by all concerned with the testing. Copies of them should be sent weekly to the procurement authorities, to the particular manufacturer concerned, and to the government inspector at the factory. The charts should all be drawn with the same horizontal scale, representing the order of the lot represented, and should be placed one above another with a clear indication of the boundaries between them when this is practicable. Space should be left at the bottom for comments on exceptional cases and a notation of action taken with respect to such cases.

The quantities represented on the charts, from top to bottom in order, will be designated by T_o , T_D , T_M , s_r , \bar{r} , s_d , \bar{d} . The highest of these, T_o , is the most comprehensive measure of the bombing errors associated with the sights under consideration, and anyone who has time to consider only one measure should watch T_o . The next two break down the overall error into a part representing deviations from the mean point of impact (MPI) of the bombs on a flight and a part representing deviations of the MPI from the target. All these first three measures are combinations of range errors with deflection errors. Of the remaining four quantities charted, two refer to range errors alone and two to deflection errors alone, two to the MPI and two to deviations from the MPI.

Any general tendency to slipshodness and poor work in a factory is

* These illustrative charts were made up from the actual bombing data discussed in Sec. 5 and are thus mutually consistent. Though these records of flights were all derived from different sights, they were arbitrarily grouped into consecutive pairs, representing fictitious single sights, and these pairs were again grouped into consecutive pairs representing samples from hypothetical lots, just as if the plan here presented had been in effect. The last flight was omitted so as to leave 64 flights, a multiple of 4, as is required by this plan. The result is to give a reasonably good illustration of the kind of charts that can be expected in test bombing of the kind carried out with bombsights of the same general quality as the ones then tested.

more likely to be observed in rising curves in the upper charts, approaching and passing the control limits, whereas light on specific faults is to be sought by casting the eye downward gradually to the lower charts.

The seven quantities to be charted will be defined in the following paragraphs, beginning with the simplest. They will therefore be in a different order from that above. The actual ordinates are not proportional to the quantities mentioned above, except \bar{r} and \bar{d} , but to their logarithms. Consequently, arithlog (that is, semilogarithmic) paper should be used for the top five charts to save the trouble of looking up logarithms. Also, the vertical scales on these five top charts are to be marked on the left with numerical values equal to the squares of the T 's and s 's since, as will be seen later, this avoids the labor of extracting square roots. The T 's and s 's themselves are given on vertical scales at the right of these charts.

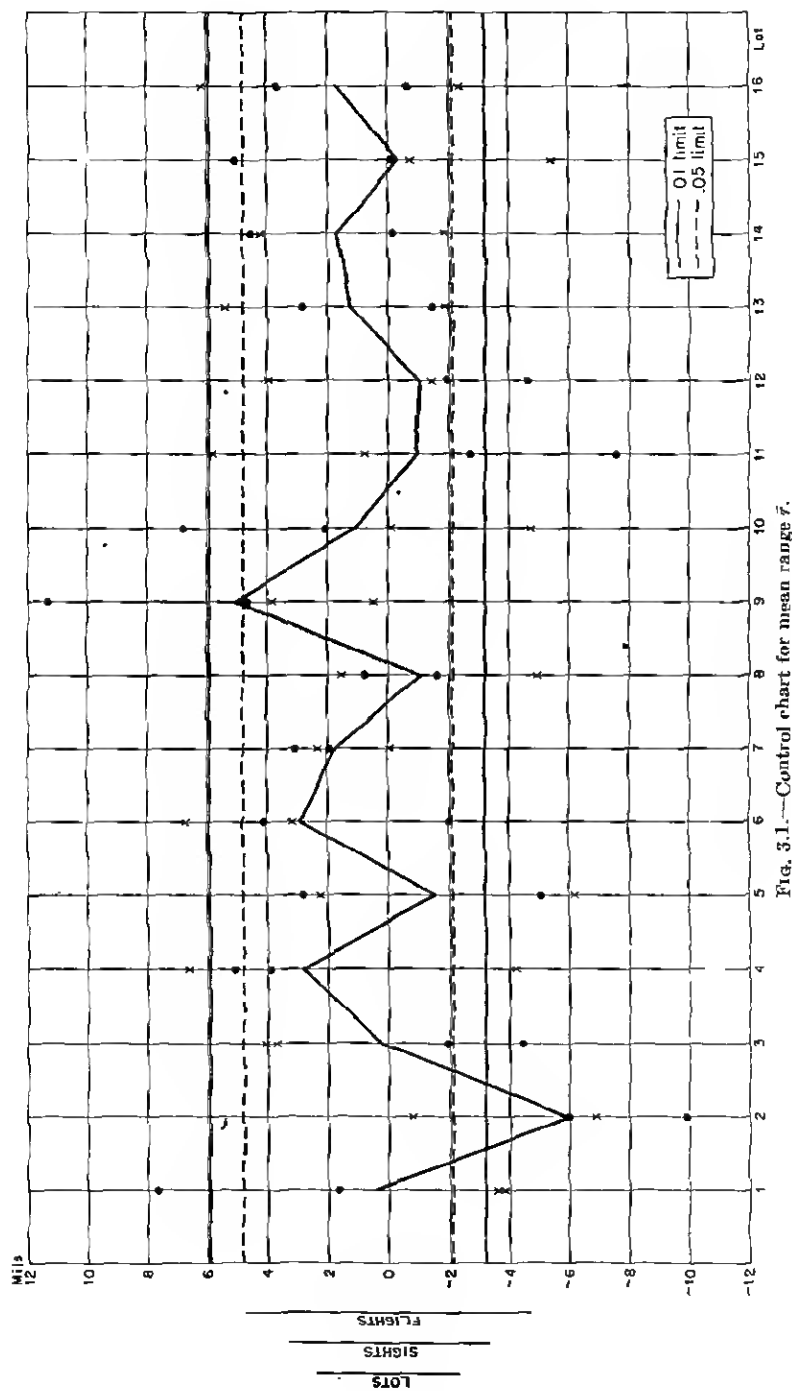
We shall use r and d as symbols for range and deflection errors, respectively, in mils,* and indicate by S the sum over the N ($=4$) bombs in a flight of the values of the expression following S .

All the numerical coefficients, yardstick lengths, and control limits herein specified should be revised periodically as further experience accumulates; they will especially need to be revised after any change in technique has been in effect long enough to provide a sufficient basis in experience. Formulas for revision will be found in Sec. 3.

2.2.2. Control Chart for Mean Range.—The control chart for \bar{r} , illustrated by Fig. 3.1, represents $\bar{r}_F = Sr/N$ for each flight by a cross or a circle. For each lot the values of \bar{r}_F found from the two flights of the sight produced earlier than the other are represented by circles, while those for the sight produced later are represented by crosses. The mean of these four values of \bar{r}_F is \bar{r}_L , the mean of the range errors for the lot. The points representing \bar{r}_L for successive lots are connected by straight lines.

Control limits are shown as two pairs of horizontal lines. The probability that a lot of sights constituting a random sample from the same population as the sights tested in the base period, with the same distribution of errors of all kinds as in the test period, should be represented by a point outside the outer control limits is 0.01. The probability that such a lot should yield a value of \bar{r}_L falling outside the inner control limits under the same conditions is 0.05. The upper and lower limits corresponding to each probability are at equal distances, not from the zero line, but from a line representing the range error in the MPI of all the bombs dropped in the base period. This point is discussed in Sec. 3.2, where the formulas and numerical values for the control limits are also

* A mil is an angular measure approximately equal to 1/6,400 of 360 degrees or to 1/1,000 of a radian, the exact definition varying from one usage to another.

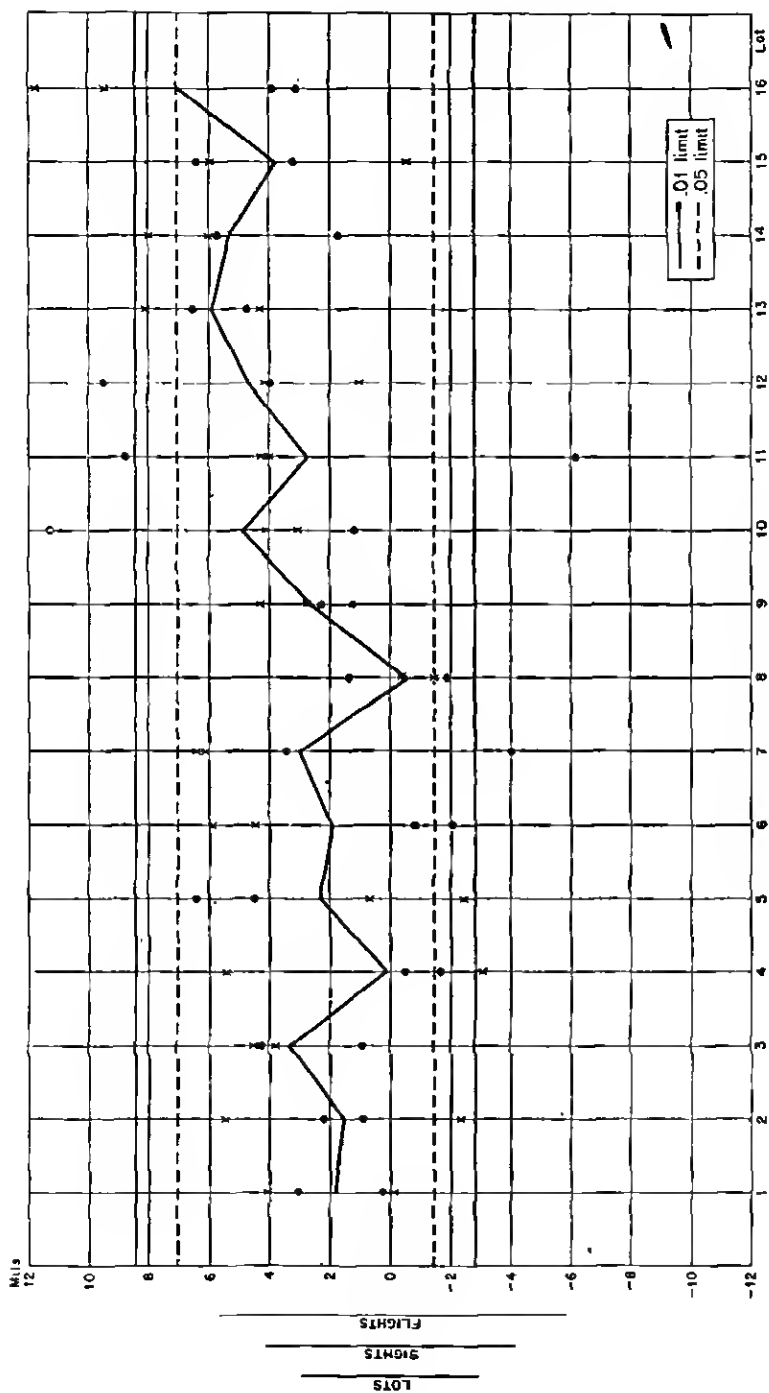
Fig. 3.1.—Control chart for mean range \bar{x} .

given. The 0.01 limits are represented by solid lines at 5.89 and -3.20 mils; the 0.05 limits are shown by lines of dashes at 4.80 and -2.11 mils.

If the zigzag line should get outside the band marked out by the inner control limits, this fact may be taken as a warning to be alert for any further indication of faults tending to make bombs fall consistently too far short of or too far beyond the target, as the case may be. If the outer control limits should be surpassed, the warning is more emphatic, since this will happen only once for 100 lots if there are only the same sources of range error as in the base period. An instance of exceeding the outer control limits should be made the occasion of an investigation at the proving ground to determine the cause. A definite trend upward or downward in the plotted quantity is another indication of a dangerous condition, even before the inner control limits are reached. In such contingencies, unless the trend or the excessive value of \bar{r}_L is definitely attributed to faults of the airplane, personnel, or other cause independent of the quality of the sight, the manufacturer should be warned promptly. It is particularly important to give early warning of trends in order that there may be an opportunity to correct gradually developing faults before they become serious. Action to be taken when control limits are passed is specified further in Sec. 2.3.

The control limits refer to \bar{r}_L but serve a secondary purpose also with respect to \bar{r}_S , the mean of the range errors for a sight, represented by a point that is ordinarily not marked but that can be estimated visually from a pair of crosses or of circles. The control limit having probability 0.01 of being exceeded by \bar{r}_L has a probability approximating 0.20 of being exceeded by \bar{r}_S , and that having probability 0.05 for \bar{r}_L has probability practically 0.33 for \bar{r}_S , provided the number of bombs dropped in the base period is large, say 200 or more. Thus the fluctuations of range error in MPI can be followed visually with a fair idea of the relevant probabilities.

To facilitate further the continuing comparison of means of range errors, a yardstick is provided at the left for the difference between the means of two lots, a longer yardstick for the difference between the means of two sights, and a still longer yardstick for the difference between the means of two flights. The vertical distance between points representing means of any of these types should exceed the length of the corresponding yardstick about once in 20 times if chance alone is operating. The means for the sights are not shown but are easily inferred as the centers of gravity of the two points representing the flights with the individual sight. A visual appraisal of the distance between these centers of gravity for the two sights representing a lot, in comparison with the middle yardstick, will usually indicate clearly whether the difference in performance in this respect is unusually great. An excessive difference should be regarded as a tentative indication of some variation of conditions at the

Fig. 3.2.—Control chart for mean deflection \bar{d} .

factory during the production of the lot represented by this sample. However, it might also be explained by a difference in weather or personnel conditions between the two days on which one sight was tested and the two days on which the other sight was tested; or by chance alone for every twenty such comparisons if these were to be made for *all* pairs. The yardstick lengths on the \bar{r} chart are 9.47, 6.70, and 4.74 mils for flights, sights, and lots, respectively.

A fallacy that must be guarded against in connection with the yardsticks is a tendency to select the greatest and the least of a series of observations and to regard them as significantly different if their heights differ by more than the length of the yardstick. This is wrong and likely to lead to far too many judgments of significant difference, because the yardstick lengths are determined on the assumption that they will be used for comparing only observations selected in a manner independent of their magnitudes. It is perfectly legitimate to use the yardstick to compare consecutive observations, or the first and last of a considerable series, though even so it must be remembered that significance will emerge fallaciously about once in 20 times. The detection of trends in quality should be facilitated by applying the yardsticks to observations a considerable distance apart. Discontinuous changes may become evident when two consecutive observations differ by an amount approximating the length of the yardstick, provided earlier observations are fairly well in accord with the first of the pair and later ones with the second. It is possible to devise exact statistical criteria for both trends and discontinuities, but workers in quality control stress the value of graphic devices.

2.2.3. Control Chart for Mean Deflection.—A control chart for \bar{d} (Fig. 3.2) should be kept in exactly the same way as that for \bar{r} . However, the control limits will be farther apart in the case of the \bar{d} chart and the yardsticks longer because the variance of deflection errors is greater than that of range errors. The 0.01 control limits are at 8.40 and -2.79 mils; the 0.05 limits are at 7.05 and -1.44 mils. The yardstick lengths are 11.65, 8.24, and 5.83 mils.

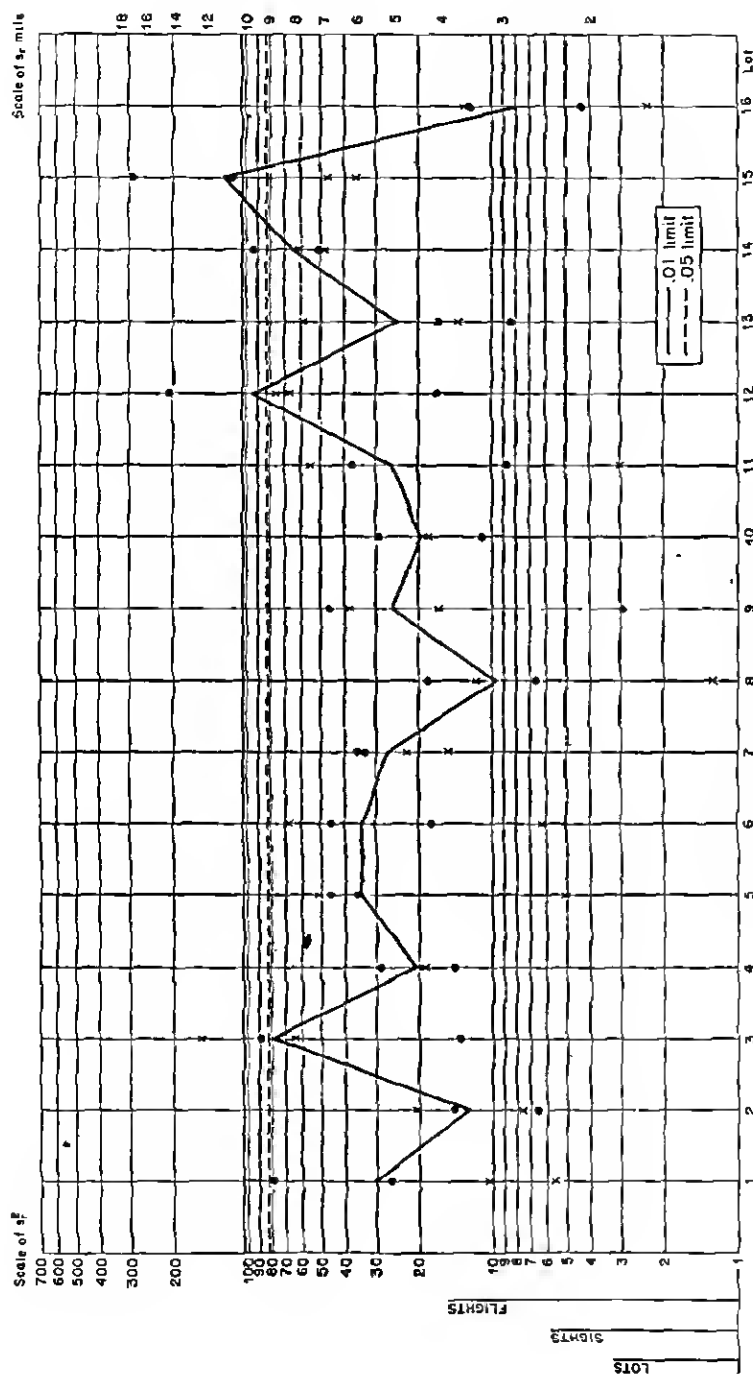
2.2.4. Control Chart for Range Variance.—For each flight the estimated variance of range errors is defined by the formula

$$s_r^2 = \frac{S(r - \bar{r})^2}{N - 1}$$

but may be found with a slight economy of labor by using the fact that

$$S(r - \bar{r})^2 = Sr^2 - \bar{r}_r Sr$$

The control chart for range variance is to be on logarithmically ruled paper (Fig. 3.3). Values of s_r^2 for the four flights representing each lot

Fig. 3.3.—Control chart for range variance s_r^2 .

of bombsights are plotted on the same vertical line, two circles for that one of the sample sights of the lot produced earlier, and two crosses for the other. The arithmetic mean of these four values of s_r^2 is the best estimate of range variance for this lot of bombsights. The points representing such means (which, because of the logarithmic scale, are slightly above the centers of-gravity of the points representing individual values of s_r^2) are connected by a zigzag line. Only a single control limit is plotted in this case for each probability considered, since it is not necessary to be on guard against unusually small variances. When $N = 4$, the variance estimate for a lot has 12 degrees of freedom (3 for each of the 4 flights). The lot variance for range that will be exceeded by chance once in 20 times is, according to the estimate supplied by our preliminary sample, 82.87, and this is represented by the height of the control limit marked 0.05 in Fig. 3.3. The corresponding value for probability 0.01 is 104.4 (see Sec. 3.3.1 for the origin of these values).

It should particularly be observed that the denominator of each of the estimates of variance here used equals the number of degrees of freedom, not the sample number. Using the sample number, as is often done, introduces unnecessary complications into the determination of the probabilities, and if applied in the present case is likely to lead to large errors.

Yardsticks having functions similar to those of Figs. 3.1 and 3.2 are provided at the left of Fig. 3.3. The logarithmic vertical scale of Fig. 3.3 makes possible the use of these yardsticks, which are to be regarded as subject to rigid translation. The exact comparison of estimates of variance in terms of probability must be made by means of a function of their ratio, or the difference of their logarithms. This is the reason for using a logarithmic chart for s_r^2 . In the charts for \bar{r} and \bar{d} an arithmetic scale was used, since the comparison between two means must be made in terms of their difference, not their ratio. The lengths of the yardsticks for flights, sights, and lots correspond, respectively, to the variance ratios 15.45, 5.82, and 3.28.

To illustrate the use of these yardsticks, suppose that s_r^2 should have the value 10 for one lot and 40 for the next. Both points are well within the control limits. But the ratio 4 exceeds the yardstick 3.28, as is immediately obvious when the points are charted, to such an extent that the probability is considerably less than 0.05 of the variances deviating so far from equality by chance alone. Unless some explanation connected with the testing is forthcoming, this is to be regarded as a danger signal suggesting deterioration of the sights in a manner leading to wider scatter in range. The two sights belonging to the lot showing the variance 40 should be examined for sources of excessive range variance such as loose rate knobs, and any explanation found should be indicated in the space below the control charts reserved for notes.

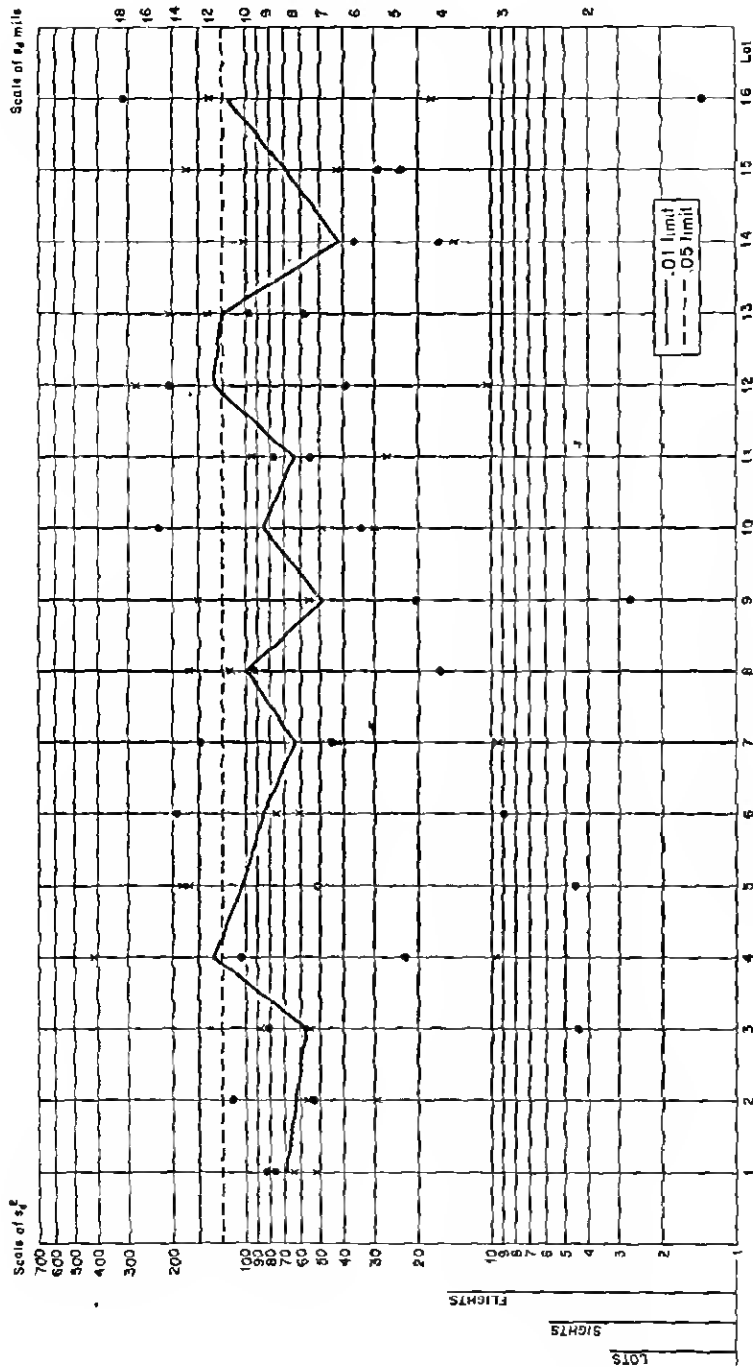


FIG. 3.4.—Control chart for deflection variance σ_d^2 .

2.2.5. Control Chart for Deflection Variance.—The variance of deflection errors is to be treated in exactly the same way, except that the control limits are in this case at 125.4 and 157.9. The yardstick lengths are the same as for the range-error variance chart (see Fig. 3.4).

2.2.6. Control Charts Combining Range with Deflection.—The indicators of quality to be used combining range and deflection errors are denoted by T with the following subscripts:

O for an over-all measure

M for a measure based only on the mean point of impact (MPI)

D for a measure based on deviations from the MPI

A second subscript will also be used when needed to make the meaning clear, as follows:

B for an individual bomb

F for all the bombs dropped in a flight

S for the bombs dropped with the same sight

L for the bombs dropped with the sights representing a lot

It will frequently be convenient to omit the second subscript.

The definitions of the various T 's all make use of the same coefficients a , b , c , whose values may be taken at first, on the basis of the experience analyzed in Sec. 5, as follows:

$$a = 0.021\ 724 \quad b = 0.001\ 331 \quad c = 0.014\ 360$$

However, these values, and the corresponding control-chart limits, should be revised periodically as further experience accumulates. They will especially need to be revised after any change in technique of inspection has been in effect long enough to provide a sufficient basis in experience. Methods of revising them, and the other numerical quantities used in this part, are described in Sec. 3.1.3.

T_{OB}^2 is defined for an individual bomb as

$$T_{OB}^2 = ar^2 + 2brd + cd^2$$

and for a flight, sight, or lot as the sum of the values of T_{OB}^2 for the individual bombs involved. However, it will only be in exceptional cases that T_{OB}^2 will actually be computed, and ordinarily it will be convenient to compute T_{OF}^2 by the formula

$$T_{OF}^2 = aSr^2 + 2bSrd + cSd^2$$

where, as before, S stands for summation over all the bombs dropped on the flight. For a sight or a lot the value of T_O^2 is found by adding together its values for the several flights involved.

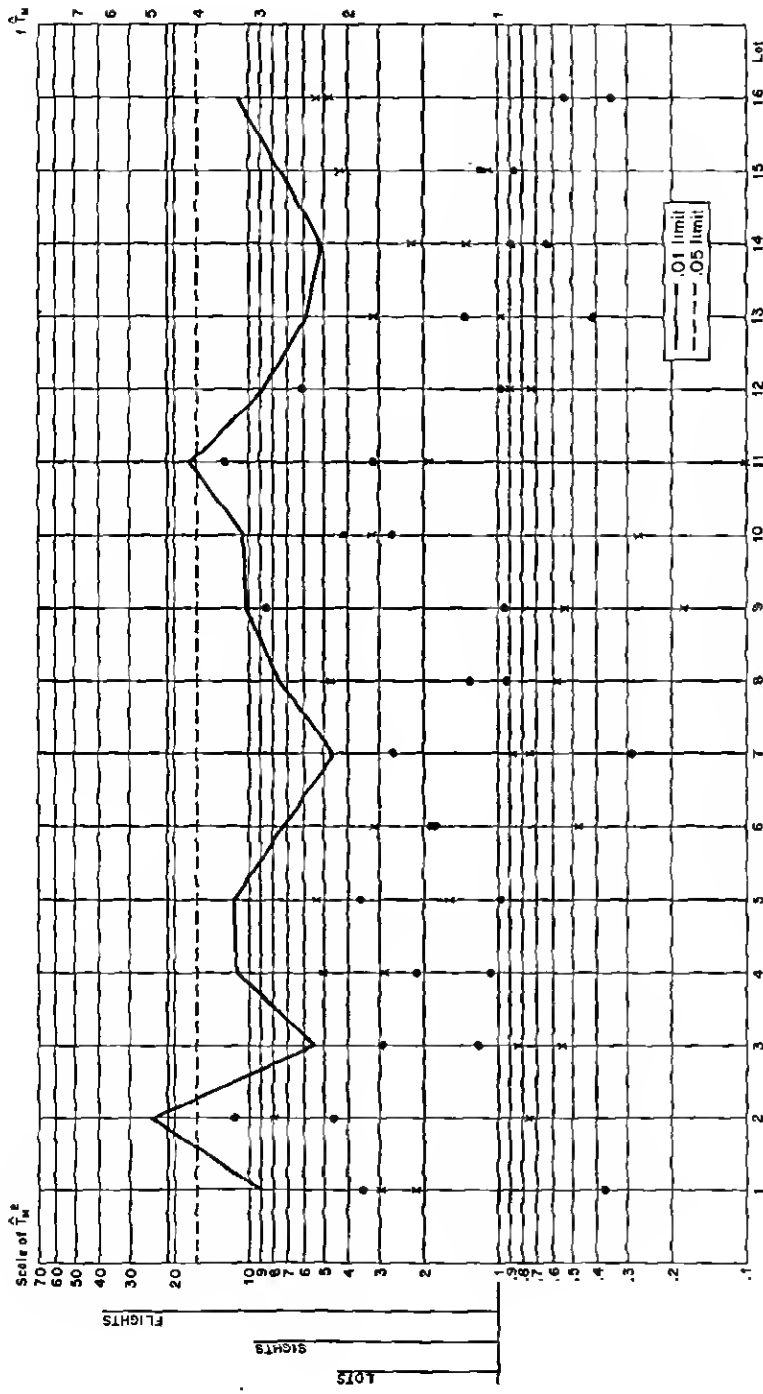


FIG. 3.5.—Control chart for error in mean point of impact T_M .

T_M^2 might be defined for a flight by the formula

$$T_{MF}^2 = N(a\bar{r}_F^2 + 2b\bar{r}_F\bar{d}_F + c\bar{d}_F^2)$$

but is more easily computed from the equivalent formula

$$T_{MF}^2 = a\bar{r}_F Sr + 2b\bar{r}_F Sd + c\bar{d}_F Sd$$

For a sight or a lot the value of T_M^2 , like that of T_o^2 , is found by adding up the values for the flights involved.

In every case T_o^2 is greater than T_M^2 . The difference is defined as T_b^2 . An algebraic identity shows that

$$\begin{aligned} T_{DF}^2 &= T_{oF}^2 - T_{MF}^2 \\ &= aS(r - \bar{r}_F)^2 + 2bS(r - \bar{r}_F)(d - \bar{d}_F) + cS(d - \bar{d}_F)^2 \end{aligned}$$

while for a sight or a lot the value of T_o^2 is the sum of those for the flights involved. Thus in every case T_b^2 depends only on the deviations from the mean points of impact for the respective flights, whereas T_M^2 depends only on these mean points of impact.

The direct use of T_M and T_o will be appropriate only when biases such as those disclosed by the statistical analysis of Sec. 5 have either been eliminated or definitely attributed to the bombsight itself rather than anything in the testing process. Until such elimination is achieved or such a judgment is reached, it is better to modify T_M and T_o so as to make them functions of deviations, not from the target, but from the mean point of impact of the bombs of the base period. Indicating this correction by placing a caret over T , and using \bar{r}' and \bar{d}' for the coordinates of the mean point of impact of the bombs of the base period, gives

$$\begin{aligned} \hat{T}_{oF}^2 &= \frac{aS(r - \bar{r}')^2 + 2bS(r - \bar{r}')(d - \bar{d}') + cS(d - \bar{d}')^2}{1 + \frac{1}{n'}} = \frac{T_{oF}^2 + U}{1 + \frac{1}{n'}} \\ \hat{T}_{MF}^2 &= \frac{N[a(\bar{r}_F - \bar{r}')^2 + 2b(\bar{r}_F - \bar{r}')(\bar{d}_F - \bar{d}') + c(\bar{d}_F - \bar{d}')^2]}{1 + \frac{N}{n'}} \\ &= \frac{T_{MF}^2 + U}{1 + \frac{N}{n'}} \end{aligned}$$

where n' is the number of bombs in the base period and

$$U = N(a\bar{r}'^2 + 2b\bar{r}'\bar{d}' + c\bar{d}'^2) - 2[a\bar{r}'Sr + b(\bar{r}'Sd + \bar{d}'Sr) + c\bar{d}'Sd]$$

The numerical values obtained from the 260 bombs discussed in Sec. 5 give, when $N = 4$,

$$U = 0.64917 - 0.065903Sr - 0.084129Sd$$

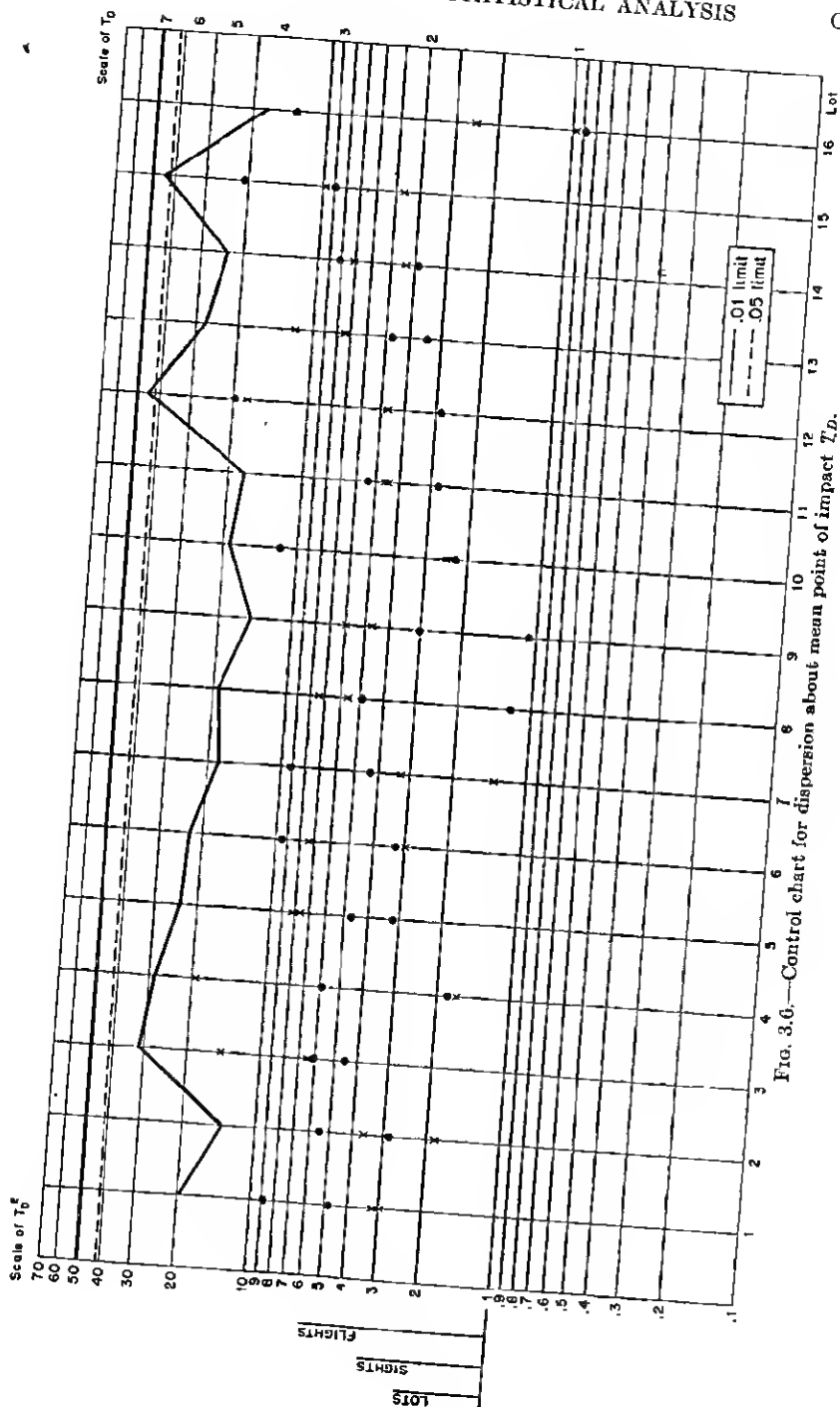


FIG. 3.6.—Control chart for dispersion about mean point of impact T_D .

For a sight or a lot, corrected values \hat{T}_0^2 or \hat{T}_M^2 are found by adding together the corresponding corrected values for the flights involved. Values of T_D are not affected by the correction.

For \hat{T}_M^2 , T_D^2 , and \hat{T}_0^2 , control charts are to be maintained on arithlog paper in a similar form to those for s_r^2 and s_d^2 (see Figs. 3.5, 3.6, and 3.7). However, there is one difference in form: The zigzag line on each T chart plots the *sums* of the quantities represented by circles and crosses, instead of the means as on the s^2 charts. This results in all the quantities plotted being of kinds customary in statistical theory, and hence easily looked up in probability tables, at least to an approximation. A further advantage of this arrangement is that it renders the appearance of the T charts so unlike that of the s charts that they cannot be confused.

On each of the T charts there is for each of the probabilities 0.05 and 0.01 an upper but not a lower control limit. The three yardsticks supplied in each case refer to differences, on a logarithmic scale, of sums for flights, sights, and lots, respectively, with probability 0.05. The values of T^2 for the control limits and yardsticks are given in the following table:

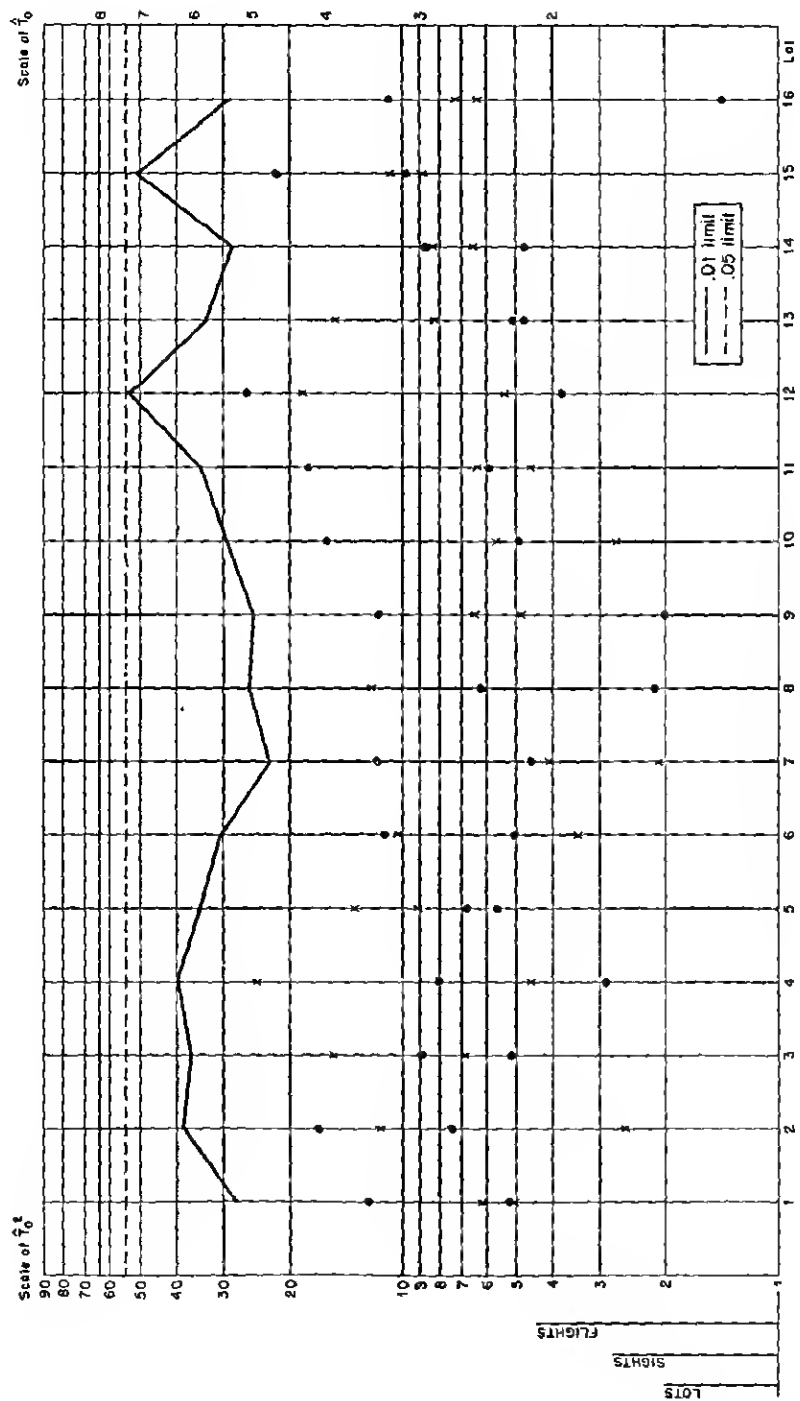
	T_M^2 or \hat{T}_M^2	T_D^2	T_0^2 or \hat{T}_0^2
0.05 control limit.	16.3	41.2	54.4
0.01 control limit.	21.2	49.4	64.0
0.05 yardsticks:			
Flights	39.0	5.8	4.4
Sights	9.6	3.3	2.8
Lots	4.4	2.3	2.0

These values require a small correction of a purely mathematical kind based on research not yet completed.

2.2.7. Illustration of the Use of Control Charts.*—A glance at Fig. 3.1 shows that all but two of the lots were well within the control limits for range MPI. Lot 9 falls slightly outside the 0.05 limit at what may be estimated as the 0.04 level. Since there is a reasonably large chance of 1 out of 15 or 16 cases exceeding the 0.05 limit, and since lot 9 shows no shortcomings on the other charts, this deviation may be disregarded.

A very different situation is presented by lot 2. As Fig. 3.1 shows, the MPI was in this case an average of nearly 6 mils short, a distance far beyond even the 0.01 control limit. Following this lot through the other control charts, we observe from Fig. 3.2 that its deflection error in MPI was very moderate, and from Fig. 3.4 that the deflection variance was exceptionally small. From Fig. 3.3 it appears that the range variance

* This section is for illustrative purposes only and is based on data put together artificially, as explained in the footnote in Sec. 2.2.1 and in Sec. 5.

FIG. 3.7.—Control chart for over-all error T_0 .

was far below the average. Moreover, in Fig. 3.3 the circles and crosses for lot 2 are all remarkably close together, indicating consistently low variance, that is, high accuracy in hitting closely around a point 6 mils short of the target. Figure 3.5 shows that the range error in MPI is too great to be concealed by averaging with the small deflection error. Upon looking at Fig. 3.6, it is apparent that lot 2 yielded the smallest value of T_D of all the 16 lots plotted, thus demonstrating a rather remarkable accuracy in hitting the wrong point. The error in MPI and the close clustering about it offset each other sufficiently so that the bombs of lot 2 are only moderately far from the target in terms of T_O , so that Fig. 3.7 shows nothing remarkable.

This combination of peculiarities might be brought about by a bombardier with very quick reactions, enabling him to keep the airplane on a remarkably good course and to maintain regularity in his behavior, but causing him to release the bomb consistently too soon. Such a man should be capable of development into an exceptionally accurate bombardier if he studied the control charts and particularly his own errors.

2.3. Action When Results Are Bad

If in any case the zigzag line crosses its 1 percent control limit, an investigation should be made of the cause of this anomaly, and the probable cause entered in the space provided for the purpose at the bottom of the control chart. If the investigation includes further air testing following shop adjustment, the same seven quantities should be computed for the new air tests and their significance judged by means of the probability formulas of Sec. 3. Entries of probable cause should indicate clearly whether the excessive bombing errors bringing about the anomaly are believed to indicate a fault in the sight or in some feature of the testing process. Pure chance may be blamed approximately once for every hundred lots from which sample sights are tested; this allotment of 1 anomaly in 100 applies separately to each of the control charts.

Some clues as to the nature of the trouble will be provided by an intelligent reading of the control chart itself, with attention to the consistency of performance of the two sights in a lot and of the two flights with each sight, and observing whether the trouble is in range or deflection, or both, and whether it introduces a bias into the MPI or increases the dispersion about the MPI. To facilitate such inquiries, a list of the types of defect likely to lead to excessive deviations in each of the seven control-chart quantities may be used (see that below, p. 140).

If the 0.01 control limits are exceeded repeatedly, the investigation should be extended to the factory. Intensified shop inspection should also be applied. In extreme cases the remaining sights in a lot represented by defective sights should be recalled or repaired. If this happens,

the shipment of further sights prior to completion of air testing of samples should be suspended until the factory has again established a satisfactory record; and the factory should revert to the status of a new factory, which implies that 40 consecutive sights should successfully pass the air test. Exact criteria as to when this should be done will need to be formulated in the future on the basis of further experience.

When the rate of production of bombsights is to be reduced, the average showing of a factory on the control charts should be taken into consideration, in comparison with that of other factories. The average value of T_0 is probably the best criterion that can be drawn from the coordinates of the bombs dropped in air testing for deciding which factory should be eliminated.

The control chart should not, however, be looked upon primarily with a view to drastic action. Its great value, demonstrated in other industries, is in detecting trends in quality and calling attention to deterioration while it is still incipient and before it becomes serious. When this value is recognized, the attitude of manufacturers changes from hostility to appreciation. In order that these desirable results be realized, it is essential that copies of control charts be transmitted promptly to manufacturers, and that attention be called to peculiarities revealed by them. Such peculiarities include not only the crossings of the 0.01 limit that call for investigations or more serious action, but also cases of exceeding the 0.05 limit more than about once in 20 times, or of progressive drifting up toward the control limits, or of excessive variation between the performances of the same sight or of two sights from the same lot, as indicated by the yardsticks. The meaning of each of the seven control-chart indicators should be made clear to all concerned.

The yardsticks are designed to facilitate visual discernment of tendencies to drift before the control limits are reached and also to help in observing abrupt changes. A little practice and familiarity with this type of chart should make it possible to detect such changes more promptly than would otherwise be easy. Prompt detection of trends and anomalous tendencies can be of great value if the factory is notified at once, since trouble can often be found and corrected in this way before it becomes serious. It is to the interest of the government and the manufacturer alike to prevent serious trouble by early corrective action of this sort, rather than to wait for it to develop to the point at which bombsights will be rejected.

Of all the indicators, T_0 is the one likely to give the sharpest discrimination between cases in which sights are really defective or the bombing for any reason poor, and on the other hand cases of pure bad luck. It combines the evidence from all the others and can serve as the deciding agent in marginal cases in which the others seem to disagree on

the question whether the bombing was good or bad. In a more specialized way, T_M combines the evidence of \bar{r} and \bar{d} , while T_D combines that of s_r and s_d . It is for diagnosis of the trouble rather than for evidence of its existence that the main reliance should be placed on the charts for means and variances.

Investigations prompted by excessive control-chart deviations will be assisted by a list of possible causes under each of the seven control-chart measures. Such a list is best drawn up by persons in continuing close relation to the manufacture, testing, and use of the sights and may need modifications from time to time with changes of model and in the testing procedure. The list below is purely tentative and needs to be supplemented by further suggestions drawn from personnel concerned with manufacture, shop testing, air testing, and maintenance.

In order that such suggestions be made intelligently, it is necessary that the personnel involved have some general understanding of the meaning of each of the seven measures. The following definitions may be sufficient for most of those concerned:

- \bar{r} Range coordinate of mean point of impact
- \bar{d} Deflection coordinate of mean point of impact
- s_r A measure of dispersion in range
- s_d A measure of dispersion in deflection
- T_M A measure of distance from mean point of impact to target, modified in accordance with probability principles to allow for the greater deflection variance
- T_D A measure of dispersion about the MPI combining range and deflection errors
- T_O An over-all measure of errors of all kinds

It should be understood that each of the T measures combines range with deflection errors, and that T_O combines all the other measures into one. If a particular defect in a sight, or in the testing process, can affect only range errors it is more likely to be detected through \bar{r} or s_r than through any of the measures that include deflection errors. In the same way, if a particular defect can affect only deflection errors, it is more likely to be found from the \bar{d} or s_d chart than from any of the T charts. However, any defect that causes *both* range and deflection errors may sometimes be detected through one of the combined T measures when it would be impossible to distinguish it from mere chance on the basis of the charts of range or deflection errors alone. Similarly, any cause affecting both MPI and variance can sometimes be brought out clearly by T_O when none of the others would make it definite.

In making up such a list, it appears better to consider the various possible sources of trouble and mark each with one or more of the seven

symbols, later rearranging to get lists in the form below, than to begin with the seven control-chart measures and try to think of all the possible causes.

The following partial and tentative list should be understood in the terms of the preceding remarks. Under each control-chart measure are listed several causes, any one of which might lead to an excessive value for the measure. Each factor is listed only under the measure or measures most likely to lead to its detection, though it may also have minor effects on other measures and will be reflected in more comprehensive measures.

\bar{x}	s_d
Grease on disk	Loose course knobs
Worn disk	Faulty directional gyro
Faulty trail plate	Stabilized sector off center
Release mechanism slow or fast	Slow reaction by airplane
Bombardier's reaction slow or fast	Slow reaction by pilot
Loose telescope cable	
Faulty sight gyro	T_M
Wrong disk speed	Any combination of factors affecting \bar{x} and \bar{d}
Loose altitude knob	Wrong altitude
Slipping of scale on altitude drum	Wrong air speed
Faulty or wrongly adjusted telescope drive governor	Faulty direction of optical axis of telescope
	Sight gyro inaccurately leveled, perhaps because of inaccurate bubbles
\bar{d}	T_D
Faulty directional gyro	Any combination of factors affecting s_r and s_d
Stabilized sector off center	Loose altitude knob
Pilot director scale displaced	Sticky bearings
Pilot director rheostat inaccurate	Variable winds
Pilot director brush worn	Poor visibility
Crosstrail mechanism inaccurate	Bumpy air
s_r	T_o
Erratic release mechanism	Any combination of factors affecting two or more of the other measures
Erratic behavior of bombardier	General slipshodness or lack of skill in either manufacture or testing
Grease on disk	Variable winds
Roller or disk not smooth	Faulty sight gyro
Roller not accurately centered	
Loose telescope cable	
Loose range knobs	
Loose altitude knob	
Faulty sight gyro	
Faulty telescope drive motor	

2.4. Experimentation

This plan may readily be adapted for efficient combination with experiments for determining the relative excellence of different models of sights and types of bombing, or for investigating other questions relat-

ing to bombing. Considerable economy in the total amount of bombing required should be obtainable by a proper design for experimenting simultaneously on various types of equipment and technique while at the same time carrying out the routine test bombing with full accuracy. The amount of bombing required will be greater than for the routine testing alone or for the experiment alone, but less than the sum of the two.

To ensure valid results from such combined enterprises, it is important to verify *before* the experiment is carried out that it satisfies the criteria of the modern statistical theory of design of experiments. It may be difficult or impossible to salvage any useful information from the results of an improperly designed experiment. Many designs are possible for efficient combined experiments. The selection of a particular design is best made in relation to the objects of a particular experiment.

As an illustration of a simple type of combination of experiment with routine testing, suppose that some new type of auxiliary equipment is to be examined (1) for its effect on the range component \bar{r} of mean point of impact, (2) as to its effect on the standard deviation s , in range, and (3) as to its effect on general accuracy. Instead of two flights per sight, four flights might now be made for a time with each sight. Two of these flights are to be on one day of a 4-day period and two on another. Of the two flights with a sight on the same day, one, chosen by tossing a coin, is to carry the new equipment and the other is not. A valid analysis of variance of range can be carried out from the results to answer question (1), and analogous procedures to answer (2) and (3) by means of s , and T_o , respectively, though the analysis for T_o must either involve approximations or wait for mathematical research on the subject to progress a little further than the point heretofore reached. The accuracy of determination of the differences made by the new equipment will be fully as great as if the entire enterprise were devoted wholly to this question. From this standpoint the information relevant to the routine testing program is obtained free of charge.

For the rating of men and equipment routinely employed in the testing of bombsights, it is possible to utilize the results without any modification of design other than objective randomization in the assignments of the various flights. This randomization should be restricted by conditions of balance and orthogonality in order to have the most accurate ratings possible and to simplify calculations, but these conditions are not essential. One simple type of rating would be merely the average of the values of T_o for the flights involved. However, the use of *new types* of equipment or personnel not used in the base period from which the control limits were determined will invalidate these control limits and should not be introduced into the air testing of bombsights

without a suitable modification of design. Similarly, altitude and other conditions attending the test bombing should be kept as nearly as possible the same as in the base period until a deliberate decision is reached that a change should be made and maintained over a considerable period. In such an event, it will be necessary to begin over again the process of accumulating data for new control-chart limits.

3. FORMULAS AND CONSIDERATIONS AFFECTING REVISIONS OF THE PLAN

3.1. General Considerations

3.1.1. Occasions for Revision.—New information and changing conditions will from time to time call for revisions of the sampling plan specified in Sec. 2. Among the changes likely to be appropriate are alterations in the size of lots, the proportion of a lot that is to be air-tested, the number of flights with each sight, the number of bombs dropped per flight, and the estimates of the variances and covariances of range and deflection errors from which control limits and yardsticks are calculated.

Another kind of change that may be developed is the use of improved types of control charts for shop inspection, together with the integration of shop-inspection procedures with air testing in a more systematic way. For such improvements the same statistical methods that are here recommended for air testing may be applied to shop testing, or to a combination of shop and air testing. Such a development would mean that instead of the two types of measurement, range and deflection errors, it would be necessary to take account of a larger number of measures on each sight and to make appropriate combinations of the various measures. The mathematical methods of multivariate statistical analysis are capable of extension with a little research to much more general situations involving coordinated testing at different stages. For this reason, and for the sake of other analogous applications, certain formulas will attain greater generality by being written in a form suitable for ready extension to more than two variables. Consequently, x_1 and x_2 will sometimes be used instead of r and d for range and deflection errors, and subscripts will be used which take only the values 1 and 2 in the present chapter but which may be understood to take other values as well in cases in which more measurements are made. For example, in place of the a , b , and c introduced in Sec. 2.2.6, when generality is sought l_{11} , l_{12} , and l_{22} , respectively, will be used, so that such a formula as

$$T^2 = ar^2 + 2brd + cd^2$$

may also be written

$$T^2 = l_{11}x_1^2 + 2l_{12}x_1x_2 + l_{22}x_2^2$$

or, more compactly,

$$T^2 = \sum \sum l_{ij}x_ix_j$$

with the understanding that the first Σ stands for summation with respect to i and the second Σ with respect to j . In this chapter, the summations will be over the values 1 and 2 only, but in the extensions envisaged they may be over any set of values. Our results will be in such forms as to be readily extended to the more general cases.

Still another type of revision of this and other sampling plans is likely to be required for sequential analysis, by which the decision as to the number of tests to be made is not fixed at the beginning of the testing but is postponed and determined by the gradually accumulating data. Considerable economies are possible by use of a well-worked-out system of sequential testing. Methods of applying sequential analysis to the particular problem of this chapter have not yet been developed.*

3.1.2. Numbers of Sightings, Flights, and Bombs.—In the plan suggested in Sec. 2, the proportion of sightings to be sent to the proving ground was taken as one-tenth simply because this has been the proportion sent in the past and because the shop-testing facilities appear to be adequate for dealing with this proportion. A continuing rating of the inspection at the factories in comparison with the results of the shop and air tests at the proving ground, and a consideration of the needs of the service, might lead to the decision to send either a larger or a smaller proportion of sightings to the proving ground. If it should be decided to increase the proportion of sightings sent to 15 or 20 percent of the total, this could be accomplished by sending 3 or 4 sightings from each lot of 20 with a minimum of disturbance of the sampling plan. If, on the other hand, it should be decided that the inspection at the factory is more adequate than has been felt to be the case in the past, and a smaller proportion of sightings is to be sent, the best way to do this would be to increase the size of the lot. It is desirable to have the lot large enough so that, with the proportion adopted, at least two sightings chosen at random from each lot shall be sent to the proving ground. The reason for this is that there should be available a continuing measure of variation within lots, and this requires at least two sightings from each lot. Such variation is displayed by the control-chart scheme of Sec. 2 along with the measures of average quality.

If the number of sightings taken from each lot should become larger, measures of this intra-lot variation could be calculated easily and accurately, but the graphic portrayal by circles and crosses might not be so clear, and vertical segments proportional to calculated measures of variation might need to be used instead. If collateral experimentation on methods of bombing, auxiliary equipment, and so forth, is to be combined efficiently with test bombing, there is an advantage in having more

* See Chap. 17 for a brief account of sequential analysis. For fuller accounts see, on applications, Statistical Research Group, *Sequential Analysis*, and on theory, Wald, "Sequential Tests."

than two sights chosen at random from each lot, as the larger numbers make possible the design of more efficient experiments. Against this consideration is to be set the fact that if the lots are large, as would be implied by having a large sample constituting a fixed percentage of a lot, there might be an excessive delay at the factory in the accumulation of enough sights to make a lot so that the random-sampling process could be applied. This objection to large lots would apply particularly where the rate of production of a factory is rather small. This matter is touched upon further in Sec. 4.2. The proportion of sights received at the proving ground to be air-tested has been arrived at not by calculation but somewhat arbitrarily from a general survey of the practices prevailing in the past and the opinions of those most closely in touch with various phases of the situation.

It is essential that at least two flights be made with each sight in order that a measure of variation due to the weather and chance factors may be available. The number of bombs dropped per flight has been taken to be four, because that was the most commonly used number in the period just before this study was begun. However, since six ore-filled test bombs can be dropped on a flight and since additional accuracy is gained by this practice, it may prove desirable to modify the plan to fit this or some other number N of bombs dropped on a flight. Increased accuracy can also be obtained by increasing the number of flights per sight. In the light of data accumulating under the sampling plan, the question of what combination of numbers of flights per sight and of bombs per flight gives the most economical method of obtaining the requisite accuracy needs to be investigated from time to time; or (what is somewhat the same thing) what combination gives the maximum accuracy obtainable with the resources available. Such a combination can only be arrived at by a study of comparative costs in conjunction with the relation of variance between flights to variance between bombs on the same flight.

3.1.3. Revision Based on New Experience.—Revision of the variances and covariance of range and deflection errors may need to be made because of changes in techniques of bombing; it should eventually be made anyhow in order to have more accurate estimates of these parameters than are at present available. From a long series of reasonably homogeneous control-chart data, the variance of range s_r^2 may be estimated as the mean of s_r^2 for the recorded flights, and the variance of deflection s_d^2 similarly. There is a need also for an estimate, which we denote by s_{rd} , of the covariance of range and deflection errors. For a single flight with N bombs such an estimate would be

$$\frac{S(r - \bar{r})(d - \bar{d})}{N - 1} = \frac{Srd - \bar{r}Sd}{N - 1}$$

but the average of these estimates over the long series should be adopted. (If N varies among the flights, the ratio of the sum of the numerators to the sum of the denominators should be used.) It is not necessary actually to compute these sums of products if all the calculations going into the control chart have been correct and are available, since the products have already been computed in the process of obtaining values of T^2 . Indeed (Sec. 2.2.6),

$$T_{DP}^2 = aS(r - \bar{r}_P)^2 + 2bS(r - \bar{r}_P)(d - \bar{d}_P) + cS(d - \bar{d}_P)^2$$

If we sum for m flights, each with N bombs, and use the expressions for s_r^2 and s_d^2 , we may solve and obtain as our new estimate of covariance

$$s_{rd} = \frac{1}{2b} \left(\frac{\sum T_{DP}^2}{m} - as_r^2 - cs_d^2 \right)$$

The number of degrees of freedom derived from each flight is $N - 1$, and, therefore from the m flights in the sample it is $m(N - 1)$. We shall put $n = m(N - 1)$. This important number, which must be used in the determination of control limits, yardstick lengths, and various tests of statistical significance, should be recorded carefully.

The revised values of the coefficients for T^2 are

$$a = \frac{s_d^2}{s_r^2 s_d^2 - s_{rd}^2} \quad b = \frac{-s_{rd}}{s_r^2 s_d^2 - s_{rd}^2} \quad c = \frac{s_r^2}{s_r^2 s_d^2 - s_{rd}^2}$$

The nature of these formulas will perhaps be clearer by reference to a more general case. If, instead of range and deflection errors, we were measuring a considerable number of features of each sight and combining these into one over-all indicator, we should use for T^2 the last formula on p. 142, with each coefficient l_i equal to the cofactor of the covariance between the i th and j th measures in the determinant of such covariances, divided by this determinant. In the formulas for a , b , and c above, the common denominator is the covariance determinant, while the numerators are the cofactors of the elements of this determinant.*

After two or three years of test bombing in a fairly uniform manner, it should be possible to obtain useful measures of seasonal variation to be applied as corrections. Even without this delay, it may be possible by a special statistical study to work out corrections of the variances to allow for the weather. The effect of any such corrections upon the number n of degrees of freedom should be noted.

* The reader unfamiliar with determinants can readily learn enough about them to carry out these instructions from the chapter on determinants in any book on college algebra, or from Chap. VII, "Determinants," in Crum and Schumpeter, *Rudimentary Mathematics*. In the determinant of the covariances s_{ij} , the elements corresponding with $i = j$ are simply variances; thus $s_{ii} = s_i^2$.

3.1.4. Assumptions Involved.—The control limits on the charts supply a test of the hypothesis that the sights of a particular lot are as good as the sights used in the base period. The limits are so determined that, if the hypothesis is true, the 0.05 limit will in the long run be exceeded approximately once for every 20 lots, and the 0.01 limit approximately once for every 100 lots. The functions plotted on the control charts have been chosen in accordance with the findings of statistical theory as those most likely to lead to these limits being exceeded if the sights tested are in fact worse than those of the base period.

These statements are, to be sure, based on a number of assumptions, but the assumptions appear reasonable. It is assumed that the different bomb drops are statistically independent or that corrections are applied that take care of any lack of independence. If the randomization procedure prescribed in Sec. 2 is followed, and especially if suitable corrections are made for weather, this assumption should fit the facts closely as regards test bombing done under the plan. Whether true independence can be ascribed to the actual bombings used in calculating the initial control limits may be questioned, since no scheme of objective randomization was in effect at the time and since no corrections were made for weather apart from the selective effect of there being no bombing in the worst weather. It is the writer's impression, based on inspection of the procedures and records, that lack of independence in these bombings is not such as to make any great difference in the control limits. The weather factor may be more serious, since the test bombings of this base period were all made in November and December. However, the charts kept at the proving ground of earlier bombings under different conditions failed to disclose any obvious evidence of any marked seasonal variation in results.

It is assumed that the bombing errors in range and deflection have a bivariate normal distribution. This assumption has a certain a priori justification in the notion of the errors resulting from accumulation of a large number of independent errors and has also an approximate a posteriori verification in various records of bombing. There is, to be sure, a slight skewness in range errors, which can be explained by a small proportion of bombs having defects that cause them to fall short with a bias peculiar to this small group. However, the deviations from normality appear to be so small as to have no appreciable influence on the final results, so far as can be judged from general statistical considerations. Certainly there is no similarity between the recorded curves of bomb distribution and the sharp-peaked theoretical ones for which mean deviations provide efficient measures of dispersion.

No assumption is made in this chapter either that correlation of range with deflection errors exists or that it does not. The records used in

Sec. 5 indicate that little or no correlation exists, though other records consisting of compilations of huge quantities of heterogeneous material do superficially indicate high correlations. The high correlations in these cases can probably be ascribed to the mixing of records of bombings at many different places and times, with various kinds of equipment, with personnel of widely different degrees of skill, together with faulty records whose complete compilation proved impossible. Even if there were a substantial correlation, it is not clear that this would be a serious detriment if the variances of the errors were moderate. The use of T^2 in the plan is equally valid whether correlation exists or not.

In selecting the T functions, it is assumed that no bias in any special direction is to be guarded against, but that equal precautions are to be taken against biases in all directions. Proofs of the optimum properties of T have been given by Hsu and by Wald.*

It is assumed also that exact probabilities are to be represented by the control limits, free from approximations of unknown degrees of accuracy. This consideration eliminates some plausible functions, such as the mean, or mean square, of the actual distances of the bombs from the target. While these functions have an intuitive appeal and seem at first glance to represent the real value of the bombsight because closeness of bomb to target is the criterion of effectiveness in action, they are not suitable for use with proof bombing. They are inefficient even for large samples by comparison with T^2_b , and for small samples they suffer from the impossibility of determining exact probabilities relative to them (see Sec. 4.8).

3.2. Means

3.2.1. Control Limits for Means.—The outer control limits for the \bar{r} chart are so chosen that, if the distribution of range errors is the same as in the base period, the probability is 0.01 that the mean \bar{r} of the range errors found with the sights of any particular lot should be represented by a point falling outside these limits. The inner control limits are determined in the same way except that the probability is 0.05. The heights of these lines in terms of the scale of mils on the chart are given by the formula

$$\bar{r}' \pm t_\alpha s'_r \sqrt{\frac{1}{n'} + \frac{1}{ghN}}$$

in which the following notation is used:

\bar{r}' = mean of range errors in base period. (Errors "over" are considered as positive, errors "short" as negative.)

s'_r = estimated standard deviation of range errors in base period,

* Hsu, "Generalized T "; WALD, "Tests Concerning Several Parameters."

consisting of the square root of the ratio of a sum of squares with n degrees of freedom to n

n' = number of range errors averaged in base period to obtain \bar{r}'

N = number of bombs dropped per flight in the period for which the control chart is to be used

g = number of flights per sight in the period for which the control chart is used

h = number of sights per lot in the period for which the control chart is used

ϵ = 0.01 for outer control limits, 0.05 for inner limits

t_ϵ = value of ratio of deviation in a mean to its estimated standard error (with n degrees of freedom) exceeded in absolute value with probability ϵ

With the additional notation

\bar{d}' = mean of deflection errors in base period (errors to the right considered positive, to the left as negative)

s'_d = estimated standard deviation of deflection errors in base period

we have the parallel formula for control limits for \bar{d}_L

$$\bar{d}' \pm t_\epsilon s'_d \sqrt{\frac{1}{n'} + \frac{1}{ghN}}$$

The base period considered in Sec. 5 yields the following numerical values:

$$\begin{array}{ll} \bar{r}' = 1.3450 \text{ mils} & \bar{d}' = 2.8046 \text{ mils} \\ s'_r = 6.8040 \text{ mils} & s'_d = 8.3686 \text{ mils} \\ n' = 260 & n = 256 \end{array}$$

According to the specifications in Sec. 2.1, $g = h = 2$ and $N = 4$. Values of t_ϵ can be found in tables of the Student distribution.* However, these tables do not extend to the value $n = 256$. For such large values t_ϵ may be obtained as the first two or three terms of the asymptotic series

$$t_\epsilon = x \left[1 + \frac{x^2 + 1}{4n} + \frac{(x^2 + 3)(5x^2 + 1)}{96n^2} + \dots \right]$$

where x is the unit normal deviate exceeded in absolute value with probability ϵ .† We thus find for $n = 256$

* See FISHER and YATES, *Statistical Tables*, Table III. This shows t_ϵ to 3 decimal places for $\epsilon = 0.001, 0.01, 0.02, 0.05$, and 0.1 to 0.9 by steps of 0.1 , for $n = 1$ to 30 by steps of $1, 40, 60, 120$, and ∞ . Also, see MERRINGTON, "Percentage Points of the t -Distribution." This shows t_ϵ to 5 significant figures for $\epsilon = 0.005, 0.01, 0.025, 0.05, 0.10, 0.25$, and 0.50 , for the same values of n used by Fisher and Yates.

† Values of x may be found from Table 1.1 in Chap. 1, provided $\epsilon/2$ is used in

$$t_{0.01} = 2.59514 \quad t_{0.05} = 1.96925$$

Substituting these values gives control limits for \bar{r}_L as follows:

$$0.01 \text{ limits: } 1.3450 \pm 4.5481 = 5.8931 \text{ and } -3.2031$$

$$0.05 \text{ limits: } 1.3450 \pm 3.4512 = 4.7962 \text{ and } -2.1062$$

For \bar{d}_L , in the same way, we find

$$0.01 \text{ limits: } 2.8046 \pm 5.5940 = 8.3986 \text{ and } -2.7894$$

$$0.05 \text{ limits: } 2.8046 \pm 4.2448 = 7.0494 \text{ and } -1.4402$$

3.2.2. Asymmetry of Control Limits and Bias in Base Period.—It may seem strange that the control limits are not symmetrical with respect to the zero line on the \bar{r} and \bar{d} charts, since sights whose use gives mean points of impact close to the target seem more desirable than those yielding more remote MPI's. A like question arises in connection with T_M and T_o . However, it should be emphasized that our comparisons are not with a theoretical ideal but with the actual performance of a base period in which the testing procedure is presumed to be comparable with that in the period for which the control chart is to be used. The material on which our records are based shows biases in both range and deflection errors in excess of any that could reasonably be ascribed to chance. Whether these biases resided in the sights, in the habits of the test bombardiers or pilots, in some other feature of the test bombing, or in the observation of the results we do not know. The sights used were accepted. If the bias was the fault of the sights, this fact should be ascertained by an *ad hoc* inquiry and the manufacturing design changed accordingly. If the bias was a result of something in the test bombing other than the sights, and if this condition continues in the period for which the control charts are to be used, it is necessary that the control limits be asymmetrical with respect to the zero line in order to avoid wholesale false alarms regarding sights that are really quite satisfactory but with which the test bombs fall moderately farther over and to the right than the average. If the proof-bombing procedure is such as to create the observed bias, a sight should be labeled unsatisfactory much more readily for bomb errors to the left and short than for errors of the same magnitude in the direction in which the bomb errors are usually made. Use of the asymmetrical limits is equivalent to applying a correction to each bomb coordinate to compensate for the bias observed in the base period.

entering the table. The value of x for $\epsilon = 0.01$ is 2.57582930, and for $\epsilon = 0.05$ it is 1.95996398.

The series for t_ϵ in terms of x is equivalent to a series for x in terms of t_ϵ given by Hotelling and Frankel, "Transformation of Statistics," and by Goldberg and Levine, " t and x "; the first two terms are also given by Peiser, "Significance Levels."

If a change in bombing procedures, or in methods of observing the positions at which the bombs fall, results in elimination or alteration of the observed bias, the control limits should be changed accordingly. Until this is done they should be based on experience.

If an investigation leads to the conclusion that freedom from bias has been achieved in the test bombing and is likely to continue, the control limits for \bar{r} and \bar{d} should be symmetrical about zero, at the same distances as from the central lines previously indicated. At the same time, \hat{T}_M should be replaced by T_M , and \hat{T}_O by T_O , both as to calculated values and in the labeling of the control chart.

Other considerations involving the fallibility of the base-period sample arise in connection with the effect on the distance between upper and lower control limits of the number of bombs in the base period. The reciprocal of this number n' is one of the terms under the radical sign in the formulas for the control limits, so that if the control limits are based on a period in which very few bombs were dropped, the limits will be relatively far apart. In such a period t_e will also be slightly larger than if numerous bombs were dropped and will push the control limits still farther apart. This fact is a consequence of our ability to make clear comparisons only with past observations. If the preliminary sample with which we compare a new sample is small, the possibility of establishing a difference when one really exists is diminished.

The effect of n' on the control limits is rather slight for numbers of any such orders of magnitude as we have been considering. There seems no reason here why the control limits should not be revised after every 200 or 300 bombs, if it is thought that fundamental conditions have changed in such an interval. A more serious objection to such frequent revision for the present is the lack of exact probabilities when n is small.

3.2.3. Yardsticks for Differences of Means.—Unlike the control limits, these yardsticks are unaffected by the bias in the MPI's of the base period. The lengths of the yardsticks for means of flights, sights, and lots are, respectively,

$$t_{0.05} \sqrt{\frac{2}{N}} s' \quad t_{0.05} \sqrt{\frac{2}{gN}} s' \quad t_{0.05} \sqrt{\frac{2}{ghN}} s'$$

where s' is to be replaced by s'_r for the range yardsticks and by s'_d for the deflection yardsticks, and the value of $t_{0.05}$ is to be determined with reference to the value of n underlying the estimates of variance in the base period. For $g = h = 2$, $N = 4$, and the same values of s'_r and s'_d used previously on the basis of experience, these expressions take the following values, which are the lengths of the yardsticks shown in Figs. 3.1 and 3.2:

	Flights	Sights	Lots
Range.....	9.4741	6.6992	4.7370
Deflection.....	11.6527	8.2397	5.8263

3.3. Variances

3.3.1. Control Limits for Variances.—The control limits on the charts for s_r^2 and s_d^2 are fixed in accordance with the distribution of the ratio of two independent estimates of the same variance. This ratio is usually denoted by F , since R. A. Fisher was the first to work with the distribution and to show its extensive usefulness in statistical work of many kinds.*

To obtain the 0.01 control limit for s_r^2 , we put $s_r^2/s_r'^2 = F$, and obtain from the table of 1 percent points the value of F corresponding to

$$n_1 = gh(N - 1) \quad \text{and} \quad n_2 = n$$

From this value of F and the value $s_r'^2$ found from the base period we obtain s_r^2 , the upper control limit. According to the plan specified in Sec. 2.1, $g = h = 2$ and $N = 4$, so that $n_1 = 12$. For the base period of Sec. 5, $n = 256$ and $s_r'^2 = 46.295$. From the tables it is found that, for $n_1 = 12$ and $n_2 = 256$, the 1 percent point of F is approximately 2.2544. Multiplying this by 46.295 gives the value 104.4 as the 1 percent control limit for s_r^2 .

The numerical values for the control limits on the s^2 scale of Figs. 3.3 and 3.4 are found in this way and given below:

	0.01 limit	0.05 limit
Range.	104.4	82.9
Deflection.....	157.9	125.4

These control limits take full account of the fact that the variances derived from the preliminary sample are not exactly those of the population but are based on 256 degrees of freedom instead of an infinite number. If the same variance estimates had been obtained from a preliminary sample of, say, 1,000,000 degrees of freedom, the control limits for range variance would have been reduced to 101.2 and 81.1, with proportionate reductions in the case of deflection.

* For a table of F , see Fisher and Yates, *Statistical Tables*, Table V, where F is called "the variance ratio." This table contains a footnote which, since it may be misinterpreted, should be disregarded in following the instructions in this chapter. A more extensive table of F is given by Merrington and Thompson, "Percentage Points of the Inverted Beta (F) Distribution."

3.3.2. Yardsticks for Variances.—The yardsticks on the variance charts have no relation whatever to the base period but depend only on the numbers of degrees of freedom in the current variance estimates that are to be compared. Their lengths are the same for the charts of range variance and of deflection variance. The vertical distance between two plotted points has probability 0.05 of exceeding the length of the appropriate yardstick if the variances plotted are obtained from samples from the same hypothetical infinite population. If F is the ratio of two such sample variances with equal numbers of degrees of freedom, $\log F$ has a symmetrical distribution extending from minus to plus infinity. The value of $\log F$ corresponding to the length of the yardstick is such that its probability of being exceeded *in absolute value* is 0.05. Hence, the probability of a random value being actually greater than this is 0.025, and the probability of its being less than the negative of this yardstick value is also 0.025. The yardstick length would thus correspond to the $2\frac{1}{2}$ percent point of the F distribution.*

For each flight the number of degrees of freedom for the differences among the range coordinates of the N bombs is $N - 1$; this is equal to the number of degrees of freedom of the deviations of these N numbers from their mean. The variance estimates for sights and for flights are obtained by adding the sums of squares of deviations from the respective flight means and dividing by the sum of the numbers of degrees of freedom. Thus the number of degrees of freedom in the variance estimate for a sight is $g(N - 1)$, while for a lot it is $gh(N - 1)$.

For the specified values $g = h = 2$, $N = 4$ the numbers of degrees of freedom for flights, sights, and lots, respectively, are therefore 3, 6, and 12. The critical values of F in these three cases are 15.439, 5.8197, and 3.2773. On the logarithmic scale of s^2 at the left of Fig. 3.3 the heights from 1 to these three numbers are the lengths of the yardsticks. On Fig. 3.4 the lengths are the same.

3.4. Comprehensive Measures

3.4.1. Control Limits for the T 's.—When the variance estimates for the base period utilize a large number n of degrees of freedom, such as the value 256 here used, the distribution of T^2 is approximately the same as the χ^2 distribution that has been tabulated and widely used for a variety of statistical purposes.† This distribution depends on a number of degrees of freedom f , which may be defined in the following manner. For each bomb the measure of discrepancy from the target

* The $2\frac{1}{2}$ percent points of F are not given by Fisher and Yates but are given by Merrington and Thompson.

† For tables of the χ^2 distribution, see Fisher and Yates, *Statistical Tables*, Table IV; or Thompson, "Percentage Points of the χ^2 Distribution."

$$T_{ob}^2 = ar^2 + 2brd + cd^2$$

has (approximately for large n) the χ^2 distribution with 2 degrees of freedom, provided the bomb is dropped under essentially the same conditions as the bombs in the base period, and provided the probability distribution is actually centered at the target without bias. The sum of any number of independent values of χ^2 has the χ^2 distribution with a number of degrees of freedom equal to the sum of the numbers for the several values of χ^2 added. Thus T_{of}^2 , the sum of the N values of T_{ob}^2 for the N bombs dropped in a flight, has approximately the χ^2 distribution with $2N$ degrees of freedom. Since g flights are made with each sight, T_{os}^2 has $2gN$ degrees of freedom, and since h flights of each lot are tested, T_{ol}^2 has $2ghN$ degrees of freedom. Since in the specific plan of Sec. 2.1, $g = h = 2$ and $N = 4$, control limits for T_{ol}^2 may be obtained approximately from the 0.01 and 0.05 probability levels for χ^2 with 32 degrees of freedom.

Under this same condition of absence of bias, $\bar{r}_F \sqrt{N}$ and $\bar{d}_F \sqrt{N}$ have the same joint distribution as r and d . Consequently

$$T_{MF}^2 = N(a\bar{r}^2 + 2b\bar{r}\bar{d} + c\bar{d}^2)$$

has, with the same approximation as before, the χ^2 distribution with 2 degrees of freedom. For the gh flights involved in testing a sample lot, the sum T_{ML}^2 of these quantities has approximately the χ^2 distribution with $2gh$ degrees of freedom. For the plan of Sec. 2.1 this means 8 degrees of freedom for T_{ML}^2 .

The distribution of a sum of squares of deviations from a mean is independent of the distribution of the mean itself when, as is assumed throughout, the fundamental distribution is of the normal form. In like manner the sum of the products of the deviations of r and d from their respective means is independent of these means in the probability sense. It follows that

$$T_{DF}^2 = aS(r - \bar{r}_F)^2 + 2bS(r - \bar{r}_F)(d - \bar{d}_F) + cS(d - \bar{d}_F)^2$$

is independent of T_{MF}^2 . Since

$$T_{DF}^2 + T_{MF}^2 = T_{OF}^2$$

and since T_{MF}^2 has 2 degrees of freedom while T_{OF}^2 has $2N$, it follows that T_{DF}^2 has approximately the χ^2 distribution with $2(N - 1)$ degrees of freedom. Since T_{DL}^2 is the sum of gh independent values of T_{DF}^2 , the number of degrees of freedom for T_{DL}^2 is $2gh(N - 1)$, a number which for the plan of Sec. 2.1 equals 24.

It is assumed in the foregoing paragraphs that r and d are free from bias. If there is a bias, the same in the new as in the old bombings,

$r - \bar{r}'$ and $d - \bar{d}'$ will be free of bias but will have variances $1 + 1/n'$ times those of r and d , respectively. (Here n' is the number of bombs in the old sample, equal to 260 for the base period considered.) Hence, if we replace r and d , respectively, by

$$\frac{r - \bar{r}'}{\sqrt{1 + \frac{1}{n'}}} \quad \text{and} \quad \frac{d - \bar{d}'}{\sqrt{1 + \frac{1}{n'}}}$$

in T_{OB}^2 , the resulting statistic

$$\hat{T}_{OB}^2 = \frac{a(r - \bar{r}')^2 + 2b(r - \bar{r}')(d - \bar{d}') + c(d - \bar{d}')^2}{1 + \frac{1}{n'}}$$

has the distribution that T_{OB}^2 would have in the unbiased case. The sum \hat{T}_{OL}^2 of Ngh values of \hat{T}_{OB}^2 therefore has the same approximate χ^2 distribution with $2Ngh$ degrees of freedom as T_{OL}^2 .

The mean range \bar{r}_F for the N bombs of a flight differs from the mean range \bar{r}' for the n' bombs of the base period by an amount whose variance is $1/N + 1/n'$ times the variance of range in general. The like is true of the difference $\bar{d}_F - \bar{d}'$. Consequently

$$\hat{T}_{MF}^2 = \frac{a(\bar{r}_F - \bar{r}')^2 + 2b(\bar{r}_F - \bar{r}')(\bar{d}_F - \bar{d}') + c(\bar{d}_F - \bar{d}')^2}{\frac{1}{N} + \frac{1}{n'}}$$

has the same approximate χ^2 distribution as T_{MF}^2 with $2gh$ degrees of freedom.

These approximate distributions require correction for the limited number n of degrees of freedom of the sample in the base period. If a base period with a value of n less than, say, 100 were taken, the correction would be substantial. As the value of n increases, the exact χ^2 distribution is approached as a limit.

No study of the exact distributions of the various T statistics here used has been published except for the simplest case. The probability that T_{OB} should exceed any assigned value T is known to be*

$$\left(1 + \frac{T^2}{n}\right)^{-\frac{n-1}{2}}$$

This is the special case for $p = 2$ of the distribution of the generalized Student ratio given by

$$T^2 = \sum \sum l_{ij} x_i x_j$$

where l_{ij} is the element in the i th row and j th column of a p -rowed symmetric matrix inverse to the matrix of sample covariances s_{ij} between x_i

* See HOTELLING, "Generalization of Student's Ratio," formula (26).

and x_i found in a former sample with n degrees of freedom for each of the p variates. The element of probability for this generalized Student ratio, namely,

$$\frac{2\Gamma\left(\frac{n+1}{2}\right)}{\Gamma\left(\frac{p}{2}\right)\Gamma\left(\frac{n-p+1}{2}\right)} \frac{T^{p-1}dT}{n^{p/2}\left(1+\frac{T^2}{n}\right)^{(n+1)/2}}$$

approaches that for χ with p degrees of freedom when n increases. The probability integral of this distribution may be evaluated in various ways, one of which is to use the asymptotic expansion*

$$\chi^2 \sim T^2 \left[1 - \frac{p+T^2}{2n} + \frac{4-p^2+(2+5p)T^2+8T^4}{24n^2} \dots \right]$$

in conjunction with the χ^2 distribution. From it may be obtained the asymptotic expansion for T^2 in terms of χ^2 , namely,

$$T^2 \sim \chi^2 \left[1 + \frac{p+\chi^2}{2n} + \frac{7p^2-4+(13p-2)\chi^2+4\chi^4}{24n^2} \dots \right]$$

This formula is particularly suitable for determining the values of T^2 corresponding to any particular probability level from those already tabulated for χ^2 .

Probabilities connected with the T distribution, or values which will be exceeded with assigned probabilities, can also be evaluated by means of the transformation

$$T^2 = \frac{npF}{n-p+1}$$

where F has the variance ratio distribution, of which tables are available, with $n_1 = p$ and $n_2 = n - p + 1$ degrees of freedom. This method is particularly suitable for small values of n .

This known T distribution may be used temporarily as an approximation for the distributions of the T statistics used in the plan presented in this chapter. It has been so used in obtaining the control limits listed in Sec. 2.2.6, which are shown in Figs. 3.5, 3.6, and 3.7. For this approximation the p of the foregoing formulas is replaced by the number of degrees of freedom f , which in Sec. 2 has the values 8, 24, and 32 for T_{ML} , T_{DL} , and T_{OL} , respectively. In general, f equals $2gh$, $2gh(N-1)$, and $2ghN$ for these several cases.†

* See HOTELLINO and FRANKEL, "Transformation of Statistics," p. 96.

† An article on the mathematical theory of this chapter, which is expected to appear in the *Annals of Mathematical Statistics*, will include the exact distribution of these T 's.

3.4.2. Yardsticks for the T^2 's.—The values of T^2 obtained from different flights are not exactly independent in the probability sense, since they involve the same values of a , b , and c , which are subject to the sampling errors of the base period, which will be small if n is large. For this reason it appears that the several values of T^2 will have positive correlations, but that these will be very small when n is as large as in the sample here considered. Apparently no great error will be made by assuming independence.

Pending the development of a more exact treatment, we may obtain yardsticks for the T charts by assuming independence and attributing to each T the χ distribution. The ratio of two independent values of T^2 , each with f degrees of freedom, has thus approximately the distribution of the ratio of two independent values of χ^2 , that is, F , with $n_1 = n_2 = f$. Since yardsticks are desired with a probability 0.05 of being exceeded in length on the logarithmic scale, the tables of the 2½ percent points of F may be used. The values of f for single flights are $2N$, 2, and $2(N - 1)$ for T_a , T_M , and T_b , respectively. These values of f are to be multiplied by g for sights and by gh for lots.

4. BACKGROUND AND REASONS FOR THE PLAN

4.1. Objectives of Sampling Inspection

Apart from special experimental and exploratory purposes, two principal objects can be gained efficiently by means of routine inspection and testing of small samples, and a third object can at the same time be attained in a somewhat less adequate fashion. From small samples it is possible

(1) To judge efficiently the general level of quality of the product of a factory or a part of a factory over a period, in comparison with the output of other productive units, and of the same unit at other times.

(2) To detect promptly irregularities, trends in quality, and deviations from customary levels.

(3) To select and reject individual bad articles, or bad lots. This function is often considered the primary one. However, the efficiency of small samples for this purpose, when the proportion of defectives that can be tolerated is small, is not so satisfactory as is sometimes imagined. This has been brought out in a recent article, "Rational Sentencing," by Dr. E. H. Sealy.

On the basis of the small samples (5 to 10 per lot of 2,000) which it is possible to fire at ammunition proof, it is quite impossible to distinguish between the qualities of individual lots, or to sort out individual bad lots from the bulk in any but the grossest cases. Proof specifications of the type which state that a lot will be accepted if its proof is clear and rejected or reproofed if certain defects appear at proof have very little effect upon the quality of the bulk being inspected.

This has often been demonstrated in cases where the test is nondestructive by 100 percent inspecting the bulk both before and after proof. The percentages defective found at 100 percent inspection of the accepted and rejected lots are almost invariably found to be nearly equal and both very little different from the percentage of defectives in the original bulk presented for proof. In other words, the quality of the product passed into the service under such a sentencing system is practically that which happens to be made at the factory. . . .

It is, then, quite impracticable to attempt to discriminate between individual lots by means of a small sample proof. What we *can* get, however, from such a proof is a knowledge of the average, over-all quality of the product of any given factory, for the accumulation of many small sample proofs amounts in time to bulk of evidence which there is no gainsaying. . . .

Broadly speaking, then, the object of rational sentencing is not to sort out individual good and bad lots but to estimate qualities assumed to be reasonably constant. If we estimate that, over a long period, a firm produces consistently a product no better than 3 percent defective, then if we need this firm's production, we must perforce accept it as a whole along with its 3 per cent of defectives, for this is the best this firm can do under its present state of knowledge and equipment. In such a case there will be, on the average, about 60 defectives in each lot of 2,000, and clearly, by chance, when picking a sample at random from a lot, one or more of these 60 defectives will from time to time be found. But it is irrational to suppose that the lots, none of whose 60 defectives chanced to be chosen in the proof sample, are any better than the others.

Dr. Sealy has elsewhere* shown the great difficulty of devising a practical *small-sample* scheme that will reduce to reasonable dimensions both the producer's risk of having good lots rejected and the consumer's risk of having bad lots accepted, when the definition of goodness is that the proportion defective in a lot shall be not more than about 2 percent. His work is, however, confined to cases in which the result of the inspection of each article is merely to classify it as defective or passable. The crudeness of this type of inspection in comparison with quantitative measurements is partly responsible for the difficulties he emphasizes. With the relatively refined statistical methods recommended in this chapter for quantitative measures of bomb-sight quality, the chances of detecting a bad lot are much greater than by the simple procedures whose limitations he points out. The fact remains, however, that too much should not be expected of small samples from the standpoint of catching infrequent defects.

One way to meet this difficulty is to increase the size of the sample by lumping together successive lots, while keeping the same proportion of inspection, so as to have larger samples. This procedure, however, introduces new and formidable difficulties. It is objectionable to keep lots of thousands on hand for the long periods required for selection and

* "Acceptance Sampling."

testing of samples; and, more fundamentally, production conditions are likely to change considerably during the accumulation and testing processes for such samples, so that the homogeneity necessary for accurate inferences is lost.

4.2. Reasons for Random Selection and for Lot Size 20

It is evident that the detection of individual defective bombsights, or small lots of bombsights, needs to be done primarily by tests in the shop rather than in the air. The main reliance for this purpose must be on the painstaking, detailed inspection of every sight made by the government inspectors at the factory. The inspection at the proving ground of 10 percent of the sights can be only a partial check on the inspectors at the factories, incapable of reliability in detection of bad small lots or individual sights in any but the grossest cases.

The real functions of testing and inspection at the proving ground must be taken primarily to be the two set forth at the beginning of the preceding section, namely, (1) the continuing appraisal of general level of quality, and (2) the detection of trends, excessive irregularity, and differences between sights produced at about the same time in the same factory.

To carry out these functions it is essential to have at the proving ground sights chosen at random. Selection of those apparently the worst, as has been done in the past, introduces not only a bias, which could be compensated by calculation after the accumulation of experience with sufficient numbers chosen at random, but the much more serious difficulty of excessive variation. To carry out accurately the two leading functions of sampling inspection on the basis of samples thus selected is practically impossible. The worst, or the least, or the greatest, with respect to any characteristic, in samples of 10 or more has a distribution far removed from that of the general population from which the samples were drawn, not only in average level, but also in variability from sample to sample and in the form of the distribution. It is these considerations that lead to the recommendation to select 10 percent of the output at random, in place of taking the worst 1 in 10.

We do not recommend taking 1 in each successive lot of 10 at random, but rather taking 2 at random from each of successive lots of 20. This might be replaced by taking 3 at random from each of successive lots of 30, or similarly with large numbers. However, the use of these larger lots would mean delay while they were being accumulated and would increase the trouble with fractions of lots remaining as tag ends with every change of model. An even more cogent objection to large lots is that the larger the lot the greater is the chance of some change in the conditions of production while it is being accumulated. Such a change means

heterogeneity within the lot, which weakens the inferences from it, and means that the existence of the change is not likely to be detected so soon as if the lots were smaller. It is particularly important that deteriorations in quality be discovered promptly, in order that further defective sights may be prevented before a great number of them accumulates. These considerations lead to a choice of size of lot as small as is consistent with having a plurality of individual sights chosen at random from it.

The use of 10 percent as the proportion of sights to be sent to the proving ground is neither defended nor opposed here but is adopted as a basis of calculation because this proportion has been used in the past.

4.3. Relation to Experimental Design

One reason for using at least two sights chosen at random from each lot is in order to obtain a ready measure of variation within the lot, so that excessive differences can be observed with the help of the yardsticks provided for the purpose and attention can thus be directed to possible heterogeneity in the productive process that might lead to deterioration. Another reason is the desirability of averaging together results from different sights of a lot in order to eliminate some of the chance variation and make trends and excessive errors more clearly discernible.

These two reasons are features of the modern theory of the design of experiments, which rests on the twin principles of replication and randomization.* Replication (*that is, repetition*) has two values. One of these is the increased accuracy obtainable by averaging the results of several observations. The other, which is of the greater importance though perhaps less obvious, is the provision of data for estimating the variance due to errors of observation, data consisting essentially of the differences between the results obtained from experiments in which the controlled conditions are the same. Knowledge concerning this error variance is necessary before any conclusion can be drawn, since real effects can only be distinguished from chance when information is available as to the distribution of the chance factor. It is true that estimates of chance variance can sometimes be drawn from other analogous experiments or from general knowledge; but such estimates are of doubtful validity when applied to a new set of data that must inevitably differ somewhat in origin from those provided by older experiments. The most satisfactory estimate of variance is that provided by the *self-contained* experiment, which is arranged from the beginning so as to

* See FISHER, *Design of Experiments*, especially Secs. 9 and 10 of Chap. 2, Sec. 20 of Chap. 3, and Secs. 25 and 26 of Chap. 4.

or alternatively by the median m , which is defined as the middle observation (when the number N is odd) when the observations are arranged in order of size. A set of N independent observations is called a "sample." If from many samples of N we form the means \bar{x} , these will have a distribution of their own, which happens to be normal also. The mean of this new normal distribution has the same value ξ as the old. But instead of the variance σ^2 , the distribution of means has for its variance the reduced value σ^2/N . This reduction in variance measures the greater accuracy in averages by comparison with single observations.

The distribution of medians from samples of N is not of the normal form but approximates it if N is large. The variance of this distribution of medians is less than that of x but greater than that of the means \bar{x} . The variance of medians is in fact approximately $\pi/2$, or 1.5708, times the variance of means from samples of the same size when N is large. The inefficiency of the median is expressed by this greater dispersion, or by considering the relative sample numbers required to obtain the same accuracy by the median as by the mean. Taking the latter point of view, and letting N_0 be the sample size to be used when the arithmetic mean is taken as the estimate of ξ , while N_1 observations (for example, bombs) are to be used when the median is taken instead of the mean, we have for the two variances

$$\sigma_{\bar{x}}^2 = \frac{\sigma^2}{N_0} \quad \sigma_m^2 = \frac{\pi\sigma^2}{2N_1}$$

If the two variances are to be equal, the ratio of the sample numbers is

$$\frac{N_0}{N_1} = \frac{2}{\pi} = 0.6366$$

Consequently, the efficiency of the median is said to be 63.66 percent. The efficiency of the mean has been demonstrated to be 100 percent; that is, its variance has the smallest possible value.

The situation is similar with respect to estimates of variance. There are infinitely many statistics whose mean values are equal to σ^2 . Among all these, the particular statistic

$$s^2 = \frac{S(x - \bar{x})^2}{N - 1}$$

(where S stands for summation over the sample) enjoys the property that its distribution has a smaller variance than any of the others. In particular, when the mean error (that is, the arithmetic mean of the absolute values of the deviations from the mean) is multiplied by a factor such that the mean value of the resulting statistic is σ , this statistic has a distinctly wider dispersion than s when the sample size is the same. Both

these statistics have distributions approaching normality of form when N is large, with the efficiency ratio

$$\frac{1}{\pi - 2} = 0.87597$$

The wide current use of the mean deviation thus has an efficiency of only about 87.6 percent. If bombs are dropped for the purpose of ascertaining their dispersion, the use of the mean deviation is equivalent to wasting about one bomb in eight.

Against this waste of bombs may be set the fact that the mean deviation is easier to calculate than the standard deviation s . The labor of calculating s is, however, much less than is sometimes supposed and is trivial if a calculating machine of any kind, or even a table of squares, is at hand. The identity

$$S(x - \bar{x})^2 = Sx^2 - \bar{x}Sx$$

means that the individual deviations from the mean need not be computed. In view of the high cost of aerial bombing, it appears definite that the use of mean deviations, and of functions of them, ought to be eliminated.*

4.6. Exact Probabilities

The standard deviation s defined above has another advantage over the mean deviation and all other methods of estimating σ in that the exact distribution of s for samples of every size, even the smallest, is a known elementary mathematical function, and tables of its probability integral are available. It also has numerous other practical advantages in more complicated situations, such as those involving least squares or the analysis of variance. In view of the small samples that must sometimes be used, the property of having readily determinable exact probabilities is a valuable one. Asymptotic formulas are somewhat dubious in application to particular cases unless a precise limit of error is at hand and are thus inferior to exact probabilities.

The choice of suitable statistics is also influenced by another and more subtle criterion of accurately determinable probabilities. This is the desideratum that in testing any hypothesis we should use probabilities that depend on nothing but the observations, together with any numbers that may be specified in the hypothesis. Statisticians have often, through lack of existence or knowledge of better methods, used formulas for standard errors and other measures of accuracy in which were involved unknown parameters. The practice has been to substitute

* See FISHER, "Mean Error and Mean Square Error." For a discussion of the general theory of the efficiency of statistics, see Fisher, "Theory of Statistical Estimation," and "Statistical Theory of Estimation."

for these parameters estimates of *them* obtained from the sample. This substitution however entails an additional sampling error not under control. Modern statistical theory has succeeded in devising various ways of overcoming this difficulty. The statistical methods recommended in this chapter all fulfill the criterion that the associated probabilities are exact, free from unknown nuisance parameters. This is true in particular of the measures T_o , T_M , and T_D combining range with deflection errors. If the new observations are from the same population as the old and if this has a normal distribution, then the distribution of each of these T 's is absolutely independent of all unknown parameters. Only the sample numbers are involved, and these are of course known. To pass from the observations to the relevant exact probabilities through these T 's is a purely mathematical operation, involving no element of judgment. It is true that the available tables do not cover fully the T distribution, so that asymptotic approximations must be used for the present, but this is a defect that can be remedied with only a little more mathematical research and calculation. The probabilities respecting T_M can be found easily and accurately from existing published tables when only one flight is involved, but the combination of these values for different flights leads to a more general distribution,* which is also applicable to T_D and T_o .

4.6. Reasons for the T Method of Combining Range and Deflection Errors

The particular method of combining range with deflection errors represented by the T formulas may be questioned. To many it will seem more natural to use measures, apparently simpler, based on the simple distances from the bombs to the target. After all, it will be said, the ultimate value of a bomb aimed at the enemy depends only on the simple geometrical distance from its point of impact to the target, and not on any figurative measure of distance that is constant along ellipses instead of circles. The simple distance has a clear meaning, intelligible to everyone. It can be measured on a map without reading off coordinates. Why not, then, use a criterion of excellence of bombing depending, in an inverse sense, only on the distances of the bombs from the target?

The several distances might be combined by simple averaging, or by taking the mean square, or in numerous other ways. Use of the mean square, or the sum of the squares, of the distances, has a special attraction in that the sum of the squares of the distances of the bombs from the target equals the sum of the squares of their distances from the mean point of impact, plus the product of the number of bombs by the square of the distance from the mean point of impact to the target. This

* This mathematical gap has been filled in since the above text was written. The results are expected to appear in the *Annals of Mathematical Statistics*.

relation, which is analogous to

$$T_o^2 = T_M^2 + T_D^2$$

makes it possible to examine separately two components of the total sum of squares that may be due to quite different causes. Furthermore, estimates of the circular probable error and similar parameters have greater statistical efficiency, that is, smaller standard errors for a given number of observations, if based on the sum of squares instead of the simple sum or mean of the distances.

But the efficiency even of the mean square circular error for estimating the general degree of dispersion is less than that of T_o or T_D , provided the base period sample is representative of the true distribution as regards the ratios of the variances of range and deflection, and as regards the correlation. If the true mean point of impact is unknown or if we choose to ignore it, the best available measure of general degree of dispersion is T_D or a function of T_D . If the true mean point of impact could be assumed to be at the target, the best measure of general degree of dispersion would be T_o or a function of T_o . Such measures have smaller variances than measures of the same parameter based on the mean square circular error in a ratio which, if we can trust the experience described in Sec. 5, is slightly less than 82 percent. This implies that the estimation of dispersion can be carried out with about equal accuracy with 82 bombs if T_D or T_o is used, or with 100 bombs if the mean square circular error is used. The simple mean of distances from the target or from the MPI, or any estimate involving mean deviations, would require distinctly more than 100 bombs to gain the same accuracy obtainable with 82 bombs when T is used.

The seemingly paradoxical result emerges that, to obtain the best possible estimate of the mean square deviation from the target to be expected in later bombing under like conditions, the mean square deviation from the target in the observed cases should not be used. Likewise, to estimate the mean deviation from the target as accurately as possible for the future, the mean deviation from the target in the past should not be used. The same is true of shooting and of all other situations in which the joint distribution of two or more variates does not have circular or spherical symmetry. Indeed, for any given set of ratios among the variances and covariances, the mean square deviation from the target and the mean deviation from the target for the population of bombs or shots, from which our observations constitute a sample, are definite multiples of a parameter measuring general degree of dispersion; and such a parameter is best estimated by a quadratic expression of the T^2 type.

For detection of bias in the mean point of impact, the use of T_M

has advantages over all other methods that have been studied.* It is true that when only a bias in a specific direction, such as that of range errors, is to be considered and it is certain that there is no bias in any other direction, the mean of the components of deviation (positive and negative) in the particular direction is the most efficient measure, while the use of a measure of bias in all directions weakens somewhat the test for a bias in the particular direction. This difficulty is, however, inescapable when there is any real importance and likelihood of errors of bias in more than one direction. If a rule were established that a bomb should be classed as "bad" if its range error were such as to be exceeded with probability 0.01 and it should also be classified as bad if the deflection error were such as to be exceeded with probability 0.01, there would be some danger of misunderstanding. Many persons would suppose that the probability of a good bomb being wrongly classified as bad under such circumstances is 0.01, whereas actually this probability is in the neighborhood of 0.02. Such erroneous ideas abound in statistical practice in many fields. Use of the combined measure T_M avoids this difficulty.

The T statistics are algebraic invariants and as such possess certain desirable properties. Any transformation of coordinates such as a rotation of axes or a change in units of measure, if applied both to the old and to the new observations, leaves each of the T 's invariant and therefore does not affect the probabilities involved. This same property of invariance is also important in obtaining the relevant probability formulas. It implies the very important fact that the probabilities associated with the T 's are exact numbers, not functions of nuisance parameters whose values are never exactly known.

There may be a thought that instead of T another invariant known as the "generalized variance" might be used.† The generalized variance has many important potential uses. However, it is not so suitable as T for the purposes here in view because, in two dimensions, it is essentially a measure of distance (in a generalized sense) from a *line* instead of from a point. While T_M and T_O can be zero only if all the bombs fall on the target, and T_D can be zero only if all the bombs fall on one point, the generalized variance will be zero if all the bombs fall on any one line, no matter how they are scattered along it. This consideration also eliminates for the present purpose several other statistics obtained by maximum likelihood methods.‡

An objection likely to be made to the T formulas is against the inclusion of the term in the product of range by deflection errors. If the

* See Hsu, "Generalized T "; WALD, "Tests Concerning Several Parameters."

† WILKS, "Generalizations in the Analysis of Variance."

‡ PEARSON and WILKS, " k Samples of Two Variables."

correlation between range and deflection in the sample in the base period were exactly zero, this term would be zero. It may be argued on a priori grounds that the true correlation is zero, and that when, as in the sample here used, the observed correlation is only slightly greater than its standard error (Sec. 5 gives, after adjustments, a correlation of -0.07535 , which is 1.2 times its standard error), later work should proceed on the fixed assumption that the correlation is zero. A further extension of this idea might lead to ignoring the difference between the variances of range and deflection, and consequently using the mean square deviation, whose inefficiency has been described above.

While omission of the small product term from T^2 would seem at first to save a little computational labor, it would lead to great mathematical complexities in connection with the probabilities. The resulting function is not an invariant, and its distribution involves as a nuisance parameter the ratio of range variance to deflection variance in the population, which is estimated by the sample only with an uncertainty that makes highly dubious any probabilities calculated on this basis. Moreover, if it should turn out that there really is some correlation between range and deflection errors, whether the causes and magnitude of such correlation are known or unknown, this correlation would constitute an additional nuisance parameter having serious effects on the accuracy of judgments based on the observations. In this connection it should be recalled that, while the particular sample here considered does not establish existence of a correlation, other reports seem, at least superficially, to show high and significant correlations between range and deflection errors in practice bombing. Some officers are of the opinion that a real correlation exists.

Another way of avoiding the calculation of products of range by deflection errors would be to make separate tests of significance for range and deflection, using the variance ratio distribution, and then to combine these by the method of combining independent test probabilities propounded by Fisher and studied by Wallis and others.* This method requires use of the exact probabilities rather than of the values of the variance ratio at a few points such as those for probabilities 0.01 and 0.05. Consequently, the tables of the F distribution must be used twice for every such test and thus for every point plotted on control charts corresponding to those for T_R , T_D , and T_o . The labor involved would amount to far more, and the assumptions necessary for validity are more stringent, by this than by the T methods.

The methods based on T are valid and accurate whether a true correlation exists or not, and whatever the ratio of the true variances may be.

* FISHER, *Statistical Methods*, Sec. 21.1 of Chap. 4; WALLIS, "Compounding Probabilities."

The only limitations on this statement are in the assumptions of normality and independence, which are made throughout, not only in the present discussion but in virtually the whole literature of bombing and firing, including that concerned with methods of combining observations. These assumptions, in relation to test bombing, are discussed in Sec. 3.1.4, pp. 146-147.

5. STATISTICAL ANALYSIS OF CERTAIN TEST BOMBINGS

5.1. Summary of the Data

In order to obtain variances in range and deflection, and a correlation, from which the coefficients a , b , c in T^2 could be found, a series of 65 flights was analyzed. These consisted of all those flights at a certain proving ground between November 4, 1942, and December 23, 1942, during which exactly four bombs were dropped. The coordinates of the point of impact of each bomb with respect to axes through the target, of which one is an average track for the whole flight, were supplied by the proving ground, together with the heading of the airplane when the bomb was dropped and other data. Two of the bombs on each flight were dropped while the airplane was moving in a generally northerly direction and the other two while it was flying in a southerly direction. The actual headings, however, varied considerably, the difference between the two in the same general direction on the same flight being commonly several degrees and in one case amounting to 25 degrees. We therefore applied to the coordinates received a rotation designed to give the errors in range and deflection with respect to the actual heading of the airplane. Table 3.1 gives the principal statistics summarizing both the original data on range and deflection and the values as adjusted by these rotations. Except for the first column of this one table, all numerical results given hereinafter will refer to the rotated values. In each case r denotes the error in range and d the error in deflection. Positive values of r refer to bombs overshooting the target, negative values of r to bombs that fall short. Deflection errors to the right are considered positive; those to the left are negative. The unit of measure is in each case the mil, about $1/1,000$ of a radian, or about $2/35$ of a degree. The data as received refer to actual impacts, uncorrected for differential ballistic wind, nonstandard altitude, nonstandard air speed, or range component of crosstrail. The actual altitudes are understood to have fluctuated rather widely about 7,000 ft., but since the errors are measured in mils the effects of these altitude variations on the results of the analysis should not be great.

If any one rotation had been applied to all the points of impact, the squared distance $\bar{r}^2 + \bar{d}^2$ of the mean point of impact from the target would be invariant. The fact that $\bar{r}^2 + \bar{d}^2$ has two different values, 8.83

for the original and 9.67 for the rotated data, results from the differences of the rotations applied for the different bombs.

TABLE 3.1
SUMMARY OF BOMBING ERRORS IN 65 FLIGHTS (260 BOMBS)

	Original (mils)	Rotated (mils)
Mean range error* (over), \bar{r}	0.5108	1.3450
Mean deflection error* (right), \bar{d}	2.9292	2.8046
Standard deviation of range errors, s_r	6.8596	6.9074
Standard deviation of deflection errors, s_d	8.7195	8.6191
Correlation of range with deflection errors.....	-0.037	-0.035

* These are means of positive and negative errors, not of their absolute values. The first two lines in Table 3.1 would give the coordinates of the mean point of impact (MPI) of all the 260 bombs if the same course had been flown in each case. They reflect biased error, whereas the next two lines give measures of the unbiased or compensating errors, often measured less accurately by the "mean deviation," or mean of absolute values of errors, which, to be comparable with the standard deviation, would need to be multiplied by a factor that for large samples approximates $\sqrt{\pi/2} = 1.253$.

Both the mean range error and the mean deflection error (that is, the means of the actual values of the errors, positive and negative, not of the absolute values) calculated from the rotated data are statistically significant relative to their standard errors. Thus it is clear that there were biased errors throwing the mean point of impact (MPI) beyond and to the right of the target. The bias in deflection could have been detected from the original, unrotated observations, but in them the bias in range, being smaller, was obscured by the addition of the variance among the four headings on the same flight to the variance due to other causes.

As in various other bombing records, the standard deviation in deflection is greater than that in range. The excess is 24.8 percent in the present sample and is statistically significant. The appropriate test is in terms of $F = (s_d/s_r)^2$, which equals 1.6158 for the original and 1.5570 for the rotated data. With the 259 degrees of freedom in each of the variance estimates, the probability that F should exceed 1.470 is 0.001. When, as here, the greater variance is divided by the smaller, the probability is less than 1 in 500 of obtaining so great a ratio of standard deviations as that actually observed if the true standard deviations are equal. At the customary 0.05 probability level, confidence limits for the percentage by which the standard deviation in deflection exceeds that in range are 12.6 percent and 38.2 percent.

The correlations -0.037 and -0.035 are completely insignificant, since their standard error is $1/\sqrt{259} = 0.0621$. This of course does not definitely prove that range and deflection errors are mutually independent; it only fails to disprove it.

Among the 65 flights there were variations with respect to both personnel and equipment. Ten different teams, each consisting of a pilot and a bombardier, were represented. The number of flights made by a team varied from 1 to 17 in the several cases. Automatic Erection System (AES) was used in 24 cases and Stabilized Bombing Approach Equipment (SBAE) in 8 cases. The distribution of the flights in relation to personnel and equipment is shown in Table 3.2. The first columns designate the pilot and the bombardier by their initials and indicate the combination of the two by a number.

TABLE 3.2
DISTRIBUTION OF FLIGHTS BY PERSONNEL AND EQUIPMENT

Pilot	Bombardier	Team number	Number of cases				
			Neither AES nor SBAE	AES only	SBAE only	Both AES and SBAE	Total for team
WT	H	1	10	5	2		17
W	S	2	6		1	3	10
R	R	3	4	3			7
W	H	4	1		1	1	3
R	H	5	7	4			11
K	U	6	1				1
K	H	7	4	4			8
K	L	8	2	2			4
W	R	9	1	2			3
K	R	10	1				1
Totals.....			37	20	4	4	65

5.2. Analysis of the Data

The primary object of the analysis was to obtain suitable coefficients a , b , and c for use in the expressions for T^2 that are to measure the accuracy of individual bombsights. However, the variances entering into these expressions are presumably affected by the variations of equipment and of personnel among the flights examined. It is to be expected that this heterogeneity will increase the sample variances above the values they would have if equipment and personnel had been kept constant on all the flights. Such an increase of variance would reduce the values of a , b , and c , and therefore the values of T^2 computed from them in future tests, giving an illusory impression of accuracy in those tests in which equipment and personnel are close to the average situation in the cases analyzed. To determine whether this is a serious bias and to correct for it if it is, it seemed desirable to consider regression equations for predicting the range and deflection errors in terms of equipment and

personnel. At the same time, the opportunity was at hand to obtain tentative estimates characterizing the performance of particular teams and of the particular types of equipment and to test the accuracy of these estimates.

Several different regression equations were used. In the first instance, to make a rather-extensive elimination of extraneous factors, we considered regression formulas with no less than 79 terms. Besides an *additive constant*, these terms were

- x_1 , defined as 1 if AES was used, and otherwise 0
- x_2 , defined as 1 if SBAE was used, and otherwise 0
- x_3 , defined as 1 if the airplane was flying north, but 0 if it was flying south
- x'_i ($i = 1, 2, \dots, 10$), equal to 1 if the bomb was dropped by the i th team, and otherwise 0. The number of variables in this group was of course 10, the number of teams.
- x''_{ij} ($i = 1, 2, \dots, 10$), equal to 1 if the bomb was dropped on the j th of the flights of the i th team, and otherwise 0. The number of variables in this group was 65, the same as the number of flights.

Two different predictands, the range and deflection errors, were used with this same set of predictors. The regression equation for estimating range error in terms of all the predictors was of the form

$$R = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + \sum_{i=1}^{10} b'_ix'_i + \sum b''_{ij}x''_{ij}$$

with a similar formula for estimated deflection error D . The coefficients were determined by the method of least squares.

It might seem that the solution of a least-square problem with 79 unknowns would be an utterly fantastic task, to say nothing of two such solutions. Yet through special circumstances it was possible not only to carry through this calculation completely, with the relevant standard errors and tests for significance in terms of probability, but to do so with a very modest amount of computing. One of these circumstances was that, because of the nature of the variables, a large majority of the elements of the matrix of the normal equations were zero. Also, a simplification was obtained through choice of 13 linear relations that can be imposed somewhat arbitrarily upon the regression coefficients because of 13 identical linear relations among the predictors, which reduce the rank of the 79-rowed matrix to 66. These 13 identical relations express the following facts:

The sum of the values of x''_{ij} for all the flights of the i th team equals x'_i . There are 10 of these relations, corresponding to the 10 teams.

The sum $x'_1 + x'_2 + \dots + x'_{10} = 1$

The sum of the values of x''_{11} for all flights using AES¹ is x_1

The sum of the values of x''_{12} for all flights using SBAE is x_2

A linear constraint corresponding to each of these was placed upon the regression coefficients in each group in order to make them determinate. Though it is customary in problems of this kind to use the simplest constraints by merely equating to zero the sum of the coefficients in each group, we chose a different set of constraints adapted to simplifying the numerical work. For example, where a constraint of the form

$$b'_1 + b'_2 + \dots + b'_{10} = 0$$

would ordinarily be imposed, we used instead

$$17b'_1 + 10b'_2 + 7b'_3 + \dots + b'_{10} = 0$$

with coefficients equal to the numbers of flights of the respective teams. This made possible a great reduction in labor because of the occurrence of this particular linear combination in the normal equations. All results of importance involving the b 's will necessarily be in terms of their differences and do not seem to be affected by replacing one such constraint by another.

The solution of the normal and constraining equations was carried out literally, in terms of symbols for the right-hand members of the normal equations, instead of numerically. In this way it was easy to obtain the two regression equations, one for range and the other for deflection errors, by substituting the two sets of right-hand members. Furthermore, the literal solution made easy the determination of standard errors and correlations among the regression coefficients in either equation. Thus it played somewhat the same role as that of the inverse matrix in least-square problems involving no identical relations or constraints.

The question whether there was significant variation among the 10 teams with regard to bias in range and deflection errors was tested by means of the variance ratio distribution. The denominator of this ratio was the estimate of variance based on the sum of squares of residuals from the regression equation. Since there were 260 observations and 79 regression coefficients connected by 13 constraints, the number of degrees of freedom for this residual variance was $260 - (79 - 13) = 194$. The numerator was a quadratic form in the b 's with 9 degrees of freedom, since they are subject to the one relation indicated above. The value of such a quadratic form can be found by first ignoring any one of the b 's (which we arbitrarily chose as b'_1), inverting* the covariance matrix of

* Several methods of numerical inversion of matrices are described in Dwyer, "Solution of Simultaneous Equations" and Hotelling, "Matrix Calculation." The method given by Dwyer is particularly valuable.

the other nine corresponding to unit variance of residuals, and then calculating straightforwardly the quadratic form of which this inverse is the matrix and in which the variables are the nine b 's used. This has only to be divided by 9 to give the numerator of the variance ratio, essentially an estimate of variance among the b 's, but differing from a mere sum of squares of their deviations from their mean because of their unequal weights and correlations resulting from the unbalanced distribution of equipment and personnel. The inverse matrix is the same for range as for deflection errors, since it depends only on the distribution of the predictors and not on the predictands.

For range errors the variance ratio F found in this way was 1.423; for deflection errors it was 1.426. These are considerably less than the value 1.923 of F that would just be regarded as significant on the customary 0.05 level and indeed are little greater than the value that would be exceeded by chance with probability 0.20 if the true mean range and deflection deviations were the same for all teams. Thus no evidence pointing to any variation among teams in these biased errors emerges from this test.

With two variates such as range and deflection errors the two separate tests may, with a substantial increase in accuracy, be replaced by a single test. In place of the foregoing variance ratios we may well consider a combined test due to Wilks.* Each variance is replaced in this test by a symmetric two-rowed determinant. The elements of the denominator determinant are the variances and the covariance of range and deflection as estimated from the residuals from the two regression equations in which they are the predictands. The numerator determinant's elements are the two quadratic forms computed from the two sets of b 's, and the bilinear form with the same matrix and involving both sets of b 's. The value 1.696 obtained for this generalized variance ratio would be exceeded by chance with a probability considerably greater than 0.05, though much further below 0.20 than in the separate variance ratios for range and deflection. Thus even this more sensitive test fails to give real evidence of variation in mean point of impact among the men engaged in dropping the bombs. That there is a real bias, at least in deflection, is easily inferred from Table 3.1 or from other bombing records. Apparently the bias is much the same for all the 10 teams on whose performance these records are based.

Application of the corresponding tests for the effect on the MPI of AES, of SBAE, and of direction of flight was much simpler because each of these effects corresponds to only 1 degree of freedom, so that the test for either range or deflection reduces merely to the comparison of a regression coefficient with its standard error. When AES was used, the MPI

* WILKS, "Generalizations in the Analysis of Variance."

was 1.6536 mils farther in the "short" direction than as if it had not been used, according to the regression coefficient, which makes allowances for effects of SBAE, direction of flight, and personnel. This coefficient is statistically significant on the customary 0.05 probability level. Since the MPI for all the bombs was 1.3450 mils "over," the use of AES appears to have been advantageous in this respect. The corresponding coefficient for deflection was not significant, and the combined test by Wilks's ratio of determinants also failed to yield a significant result on the 0.05 level. The same tests applied to SBAE gave results far from significant, suggesting no difference according as this equipment was used or not. σ

The effect of direction of flight on MPI was tested by means of the coefficient b_3 in the 79-term regression equation. For range the effect was insignificant. But for deflection the value -4.1045 was significant even on the 0.01 level. This indicates that the bias toward the right was considerably less flying north than flying south.

The variations of MPI among flights were tested by an approximate method, simpler than that used for personnel variance, which would for 65 flights with 53 degrees of freedom have involved the considerable labor of inverting a matrix of 53 rows. Such a piece of calculation is not so completely out of the question as would once have been thought, but it did not seem worth while for the present purpose. By ignoring the unbalance occasioned by disproportionate frequencies of equipment and personnel, while utilizing the balance of north and south flights and the fact that exactly four bombs were dropped on each flight, these considerations lead to the estimate $4\sum b''^2/53$ of variance among flights. This turns out to be insignificant for deflection but significant for range. The combined test for range and deflection failed to yield a significant result. Thus any important effect on MPI of variations among flights seems to be confined to the range components. Such variations refer to effects of varying weather and other factors not taken into account in the regression equation but do not include the variations of personnel and equipment considered.

Since it is to be expected that pilots and bombardiers will change from time to time, as will also the weather, the variances of deviations from the 79-term regression functions will be less relevant than if the effects of the fluctuations had not been eliminated. If the personnel were to remain constant, and of constant ability, and if an adequate measure of seasonal variation were available from records over a period of years based on ore-filled bombs, the appropriate estimates of variances and correlation for appraising bombsights under test would be in terms of deviations from a regression equation involving all these factors. The omission of the terms in the regression function corresponding to per-

sonnel may also be justified on the ground that, as seen above, no discernible differences between the MPI's of different teams have been found.

Inclusion of an allowance for equipment type does seem to be needed, first because of the highly significant difference in MPI associated with AES, and second because of the prospect that future standardization will lead either to the use or the nonuse of each of the types of equipment with all sights tested alike. Furthermore, it is to be hoped that methods will be found to eliminate the difference between the MPI of bombs dropped on northward and on southward flights. The values recommended for the coefficients a , b , and c of the test functions T^2 to be used for future control charts have therefore been based on the residuals from regression functions with only four terms. Besides a constant, these terms involved

x_1 , which equals 1 if AES was used and is otherwise 0

x_2 , which equals 1 if SBAE was used and is otherwise 0

x_3 , which equals 1 if heading was north, but 0 if heading was south

These regression equations were found to be, for range errors in mils over,

$$R = 2.9125 - 1.4457x_1 - 2.8149x_2 - 1.3746x_3$$

and for deflection, measured in mils right,

$$D = 5.4099 - 0.8106x_1 - 1.0176x_2 - 4.3615x_3$$

The deviations from either of these regression equations are 260 in number but have only 256 degrees of freedom because of the four constants in the equation, in accordance with well-known least-square theory. The sum of squares of these deviations from one of the equations, divided by 256, gives the estimated variance in range or deflection. In the same way, the sum of products of deviations from the two equations, divided by 256, gives the estimated covariance. These values are

$$\begin{array}{ll} \text{Range variance.....} & s_r^2 = s_{11} = 46.294995 \\ \text{Deflection variance.....} & s_d^2 = s_{22} = 70.033392 \\ \text{Covariance.....} & s_{rd} = s_{12} = -4.290599 \end{array}$$

From these values a simple calculation gives

$$s_r = 6.8040 \text{ mils} \quad s_d = 8.3686 \text{ mils} \quad r = -.07535$$

the estimated values mentioned in previous parts of this chapter of the true standard deviations σ_r and σ_d and correlation ρ . The number 256 of degrees of freedom is large enough to make the estimates s_r and s_d quite reliable. The standard error of each of these standard deviations is only about 4.42 percent of its value. That of r is exactly $1/16$, making

the correlation only 1.206 times its standard error. The probability of so great a value of $|r|$ in the absence of any real correlation is about 0.23, so that the hypothesis of independence between range and deflection is not refuted by these data, though there is a faint suggestion that bombs that fall short tend to fall to the right, while those going over the target tend to fall to the left.

The inverse of the matrix

$$\begin{bmatrix} s_{11} & s_{12} \\ s_{12} & s_{22} \end{bmatrix}$$

is

$$\begin{bmatrix} a & b \\ b & c \end{bmatrix}$$

and from the above values we find

$$a = 0.021724 \quad b = 0.001331 \quad c = 0.014360$$

the values used in the plan presented in Sec. 2.

5.3. Ratings of Equipment and Personnel by Test Bombing

A series of test bombings can be utilized to obtain information not only regarding the sights used, but at the same time regarding other equipment and the men who do the flying and drop the bombs. For each flight T_0^2 supplies a measure of the general success, and this is easily analyzed into the components T_M^2 and T_B^2 corresponding, respectively, to deviations of the MPI from the target and of the bombs from the MPI. By combining the values of T_0^2 (or of T_M^2 or of T_B^2) for all the flights on which a particular kind of equipment was used, or on which a particular man or team flew, and contrasting with the flights not involving the same men and equipment, it is possible to obtain ratings of personnel and equipment. Approximate probability distributions are available for testing the reliability of such ratings, since each sum of independent values of T^2 may with little error be regarded as having the χ^2 distribution, and the ratio of two such sums the F distribution. Since several kinds of equipment in addition to the personnel can thus be rated on the basis of the same bombing records, such multipurpose test bombing is relatively very economical and productive of information.

Complete validity of such ratings is, however, essentially dependent on a condition that must be provided *before* the bombings, not afterward. This condition is that, subject to whatever general restrictions are appropriate, the assignment of personnel and equipment to particular flights must be strictly at random. There is no way of doing this except by the use of the actual mechanism of games of chance, or of their equivalent in the form of tables of random numbers. In the absence of

such objective chance, the assignments must be made by human beings. Experience has clearly shown that human beings unaided by gambling equipment are unable to assign different test materials to different experimental trials in such a way as to avoid bias, either in the averages to which the experiment leads or in the measures of error that must be computed as functions of deviations from the observed averages. Consequently, the ratings of the pilots and bombardiers in Table 3.4, while historically accurate, are subject to the possibility of being explained away by features of the method by which assignments were made. This same difficulty qualifies the statistical interpretation of economic time series and other such records which, though frequently the best available guides, lack the kind of validity possible only in a well-designed experiment.

To secure *efficiency* as well as *validity* in an experiment, it is usually necessary to impose restrictions on the randomization. Thus in comparing the results of two treatments when the chance variances are the same in both cases, the standard error of the difference of the means is proportional to $\sqrt{1/N + 1/N'}$, where N and N' are the numbers to which the two treatments are applied. If $N + N'$ has any fixed value, the standard error is therefore a minimum when $N = N'$. Randomization in assignment of the cases to the two treatments should then be subject to the condition $N = N'$. This could be done by shuffling and randomly dividing a pack of cards consisting of black and red cards in equal numbers. It could not be done merely by flipping a coin once for each case, since the condition $N = N'$ might not then be satisfied. This question of efficient arrangement of experiments through restricted randomization has many ramifications, particularly where several questions, such as the efficacy of several kinds of equipment serving different purposes, are to be tested simultaneously in the same experiment.*

Values of T_o^2 , T_M^2 , and T_b^2 were computed for each of the 65 flights. Graphs of these three functions in the order in which the flights were made are appended as Figs. 3.8, 3.9, and 3.10, respectively. These figures have the general appearance of control charts. They differ, however, from suitable control charts in certain respects. Measures of quality should be plotted on a control chart in the order in which the articles are manufactured, whereas here the order is that in which the tests were performed. In this material several different series of serial numbers were represented, referring to different modifications of design and perhaps different manufacturers. It is best to run a separate control chart for each modification and for each factory.

The points in these graphs are on the average higher relative to the theoretical probability 0.20, 0.05 and 0.01 levels shown than would be

* Fisher, *Design of Experiments*, is the best treatise on this subject.

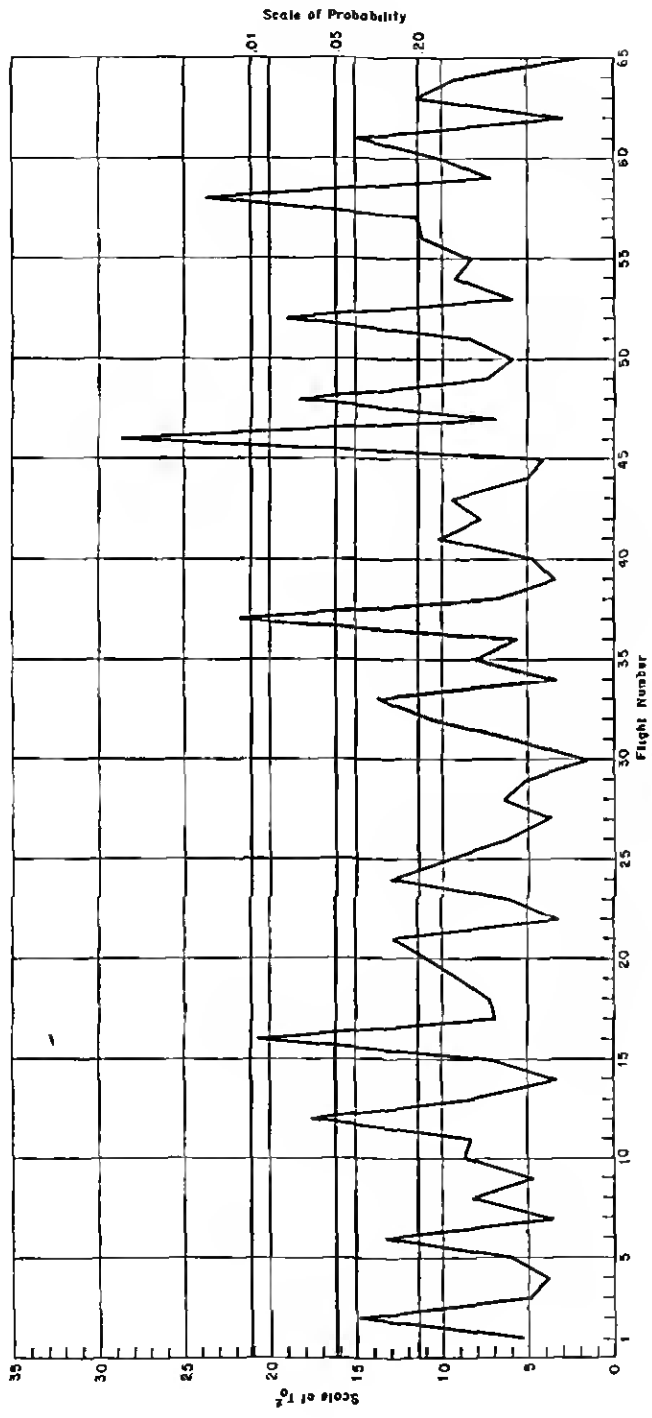


FIG. 3.8.—Over-all measure of error T_d applied to sample data.

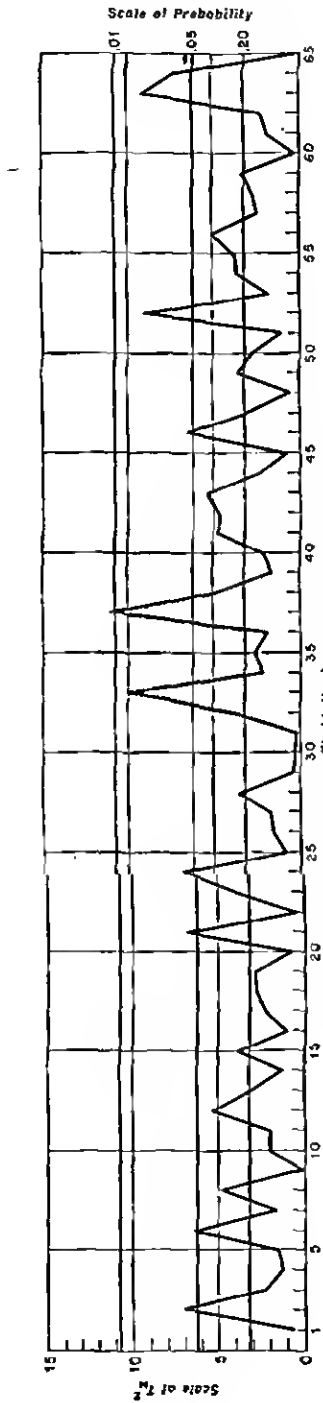


FIG. 3.9.—Errors in MPI in sample, as measured by T_M^2 .

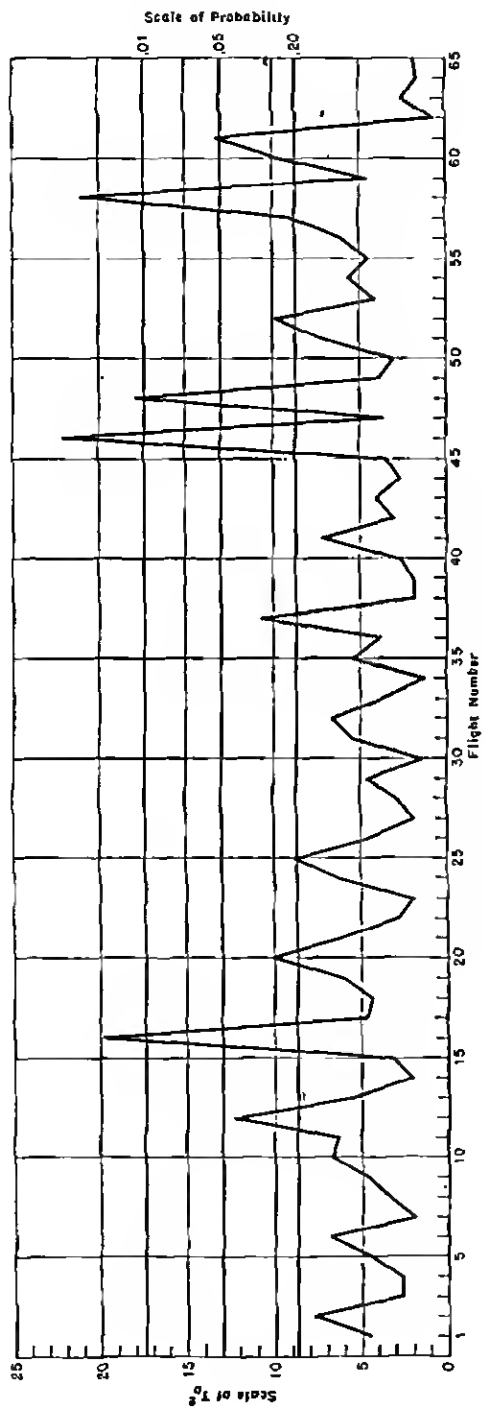


FIG. 3.10.—Dispersion measure T_D^2 applied to sample data.

expected in a manufacturing and testing routine in a state of control. The reason for this lies in a particular feature of the way the charts were constructed rather than in any shortcomings of the sights tested. The variances on which the coefficients in T^2 are based were chosen in Sec. 5.2 on the basis of deviations from 4-term regression functions, in order to eliminate from these estimates of variance the effects, which it is to be anticipated are not to continue long, of the differences between use and nonuse of the Automatic Erection System and Stabilized Bombing Approach Equipment, and between northward and southward flights. This elimination has the effect of decreasing the variances somewhat and thus of increasing the coefficients in each of the expressions for T^2 . If a , b , and c had been calculated by inverting the two-rowed matrix of sums of products of the raw deviations from the target, and if these raw deviations had then been substituted in T_o^2 , T_M^2 , or T_b^2 , the average of the resulting values would for each of these three functions be exactly the number of degrees of freedom, respectively, 8, 2, and 6. If, on the other hand, with the values of a , b , and c actually used, r and d had been replaced by the deviations from the 4-term regression functions, the averages would again in each case be exactly equal to the number of degrees of freedom. But because actual deviations were substituted for r and d while corrected variances were used in determining the coefficients, the averages exceed the numbers of degrees of freedom. Thus the average of the 65 values of T_o^2 is 9.00786 instead of 8. This is reflected graphically in the fact that the proportions of the 65 cases above the horizontal lines are in general somewhat greater than the respective probabilities.

From Table 3.3 it appears that AES and SBAE, instead of improving bombing accuracy, seemed to make it worse. The significance of this apparent effect may be tested (with an approximation equivalent to identifying the sample variances and covariance based on 256 degrees

TABLE 3.3
EFFECT OF EQUIPMENT ON OVER-ALL ACCURACY OF BOMBING
(Excellent bombing is indicated by low values of T_o^2)

	Number of flights	ΣT_o^2	Average T_o^2
Flights using AES.....	24	228.350001	9.51458
Flights not using AES.....	41	357.161062	8.71125
Flights using SBAE.....	8	79.554375	9.94430
Flights not using SBAE.....	57	505.956688	8.87643

of freedom with the true values of these parameters in an infinite population) by means of the variance ratio distribution with numbers of degrees

of freedom equal to eight times (since each flight has 8 degrees of freedom) the numbers of flights with and without the equipment in question. For AES the ratio is

$$F = \frac{9.51458}{8.71125} = 1.09222$$

with $n_1 = 192$ and $n_2 = 328$. This is not at all significant since the probability of a greater value of F is considerably more than 0.20. Actually, the relevant probability is more than double this value because of our selection of the greater mean value of T_0^2 to put in the numerator. For SBAE we have

$$F = \frac{9.94430}{8.87613} = 1.12030$$

which, with $n_1 = 64$ and $n_2 = 456$, is similarly insignificant. Thus these results do not prove that AES and SBAE have deleterious effects. They would not actually prove it in a really satisfactory manner even if the results had turned out to be significant, since the assignment of the equipment to particular flights was presumably not on the basis of objective randomization. It is entirely possible that the decision to use or not to use either of these kinds of equipment on each occasion had some relation, conscious or unconscious, to the weather, the altitude, the personnel, or some other variable affecting the accuracy.

The same qualifications apply to the average values of T_0^2 for the 10 teams shown in Table 3.4. Such scores are reliable indicators of differences in personal ability only if one of two conditions is satisfied

TABLE 3.4
VARIATION OF OVER-ALL ACCURACY WITH PERSONNEL
(Excellent bombing is indicated by low values of T_0^2)

Teams	Number of flights	ΣT_0^2	Average T_0^2
1—WQ-H	17	184.834959	10.87264
2—W-S	10	73.105782	7.31058
3—R-R	7	62.168030	8.88115
4—W-H	3	30.389824	10.12994
5—R-II	11	72.692086	6.60837
6—K-J	1	3.240875	3.24088
7—K-H	8	98.558949	12.31987
8—K-L	4	22.423547	5.60589
9—W-R	3	28.637496	9.54583
10—K-R	1	9.459515	9.45952
All flights.....	65	585.511063	9.00786

Either the assignment of the men must be suitably randomized, or an exhaustive knowledge of the other causes of variation must be at hand

and must show that these other causes exactly balanced as between the different teams. Since it is practically impossible to fulfill the second condition, objective randomization in advance is the only practical way of validating scores.

Even under randomization, differences in scores prove nothing unless they are too great to be ascribed to chance. As between any two teams selected without reference to their scores in this bombing series, the effects of chance may be examined by means of the variance ratio, equal to the ratio of the mean values of T^2_0 , with numbers of degrees of freedom equal to the numbers of flights of the two teams multiplied by the number of degrees of freedom, here 8, for each flight. However, it would be an error to compare in this way two teams selected because their scores are the greatest and the least or because they occupy adjacent places when arranged in the order of the scores. Whether the 10 scores as a whole differ significantly from one another might be determined by the application of such a criterion as Bartlett's.* The tests might also be refined, if it should seem worth while, by a more complete segregation of the effects of personnel from those of each kind of equipment, here represented by overlapping degrees of freedom, and of interactions. We are dealing here with generalizations of the ordinary analysis of variance, generalizations whose fundamental theory has been developed only part of the way necessary for an efficient analysis of the ramifications of bombing accuracy.

6. REFERENCES

- BARTLETT, M. S.: "Properties of Sufficiency and Statistical Tests," *Proceedings of the Royal Society of London*, Vol. 160A (1937), pp. 268-282.
- CRUM, W. L., and SCHUMPETER, JOSEPH A.: *Rudimentary Mathematics for Economists and Statisticians*, McGraw-Hill Book Company, Inc., New York and London, 1946, 183 + ix pp.
- DWYER, P. S.: "The Solution of Simultaneous Equations," *Psychometrika*, Vol. 6 (1941), pp. 101-129.
- FISHER, R. A.: "A Mathematical Examination of the Methods of Determining the Accuracy of an Observation by the Mean Error and by the Mean Square Error," *Monthly Notices of the Royal Astronomical Society*, Vol. 80 (1920), pp. 758-770.
- : "The Theory of Statistical Estimation," *Proceedings of the Cambridge Philosophical Society*, Vol. 22 (1925), pp. 700-725.
- : *Statistical Methods for Research Workers*, 4th and later ed., Oliver and Boyd, Ltd., Edinburgh and London, 1932-1943.
- : *The Design of Experiments*, Oliver and Boyd, Ltd., Edinburgh and London, 1935, 252 + xi pp.
- : *Statistical Theory of Estimation*, University of Calcutta, Calcutta, 1938.
- , and YATES, FRANK: *Statistical Tables for Biological, Agricultural and Medical Research*, 2d ed., Oliver and Boyd, Ltd., London and Edinburgh, 1943, 98 + viii pp.

* BARTLETT, "Sufficiency and Statistical Tests." For an account of Bartlett's test, see Chap. 15, Sec. 2.

- GOLDBERG, HENRY, and LEVINE, HARRIET, "Approximate Formulas for the Percentage Points and Normalization of t and χ^2 ," *Annals of Mathematical Statistics*, Vol. 17 (1946), pp. 216-225.
- HOTELLING, HAROLD, "The Generalization of Student's Ratio," *Annals of Mathematical Statistics*, Vol. 2 (1931), pp. 360-378.
- : "Some New Methods in Matrix Calculation," *Annals of Mathematical Statistics*, Vol. 14 (1943), pp. 1-34.
- , and FRANKEL, LESTER: "The Transformation of Statistics to Simplify Their Distribution," *Annals of Mathematical Statistics*, Vol. 9 (1938), pp. 87-96.
- HSU, P. L.: "Notes on Hotelling's Generalized T ," *Annals of Mathematical Statistics*, Vol. 9 (1938), pp. 231-243.
- KENDALL, M. G., and SMITH, B. DABINGTON: *Random Sampling Numbers*, Cambridge University Press, London, 1939, 60 + x pp.
- MERRINGTON, MAXINE: "Table of Percentage Points of the t Distribution," *Biometrika*, Vol. 32 (1942), p. 300.
- , and THOMPSON, CATHERINE M.: "Tables of Percentage Points of the Inverted Beta (F) Distribution," *Biometrika*, Vol. 33 (1943), pp. 73-88.
- PEARSON, E. S., and WILKS, S. S.: "Methods of Statistical Analysis Appropriate for k Samples of Two Variables," *Biometrika*, Vol. 25 (1933), pp. 353-378.
- PEISER, A. M.: "Formulas for Significance Levels of Certain Distributions," *Annals of Mathematical Statistics*, Vol. 14 (1943), pp. 56-62.
- ROY, S. N.: " p -Statistics, or Some Generalizations in Analysis of Variance Appropriate to Multivariate Problems," *Sankhya: The Indian Journal of Statistics*, Vol. 4 (1939), pp. 381-396.
- SEALY, E. H.: *Rational Sentencing of Proof Results*, (British) Ministry of Supply, Advisory Service on Quality Control, Technical Report No. Q.C./S/6, October 20, 1943.
- : *Acceptance Sampling*, address given to the Industrial Applications Group of the Manchester Statistical Society on May 20, 1944, mimeographed, British Central Scientific Office, July 14, 1944.
- Statistical Research Group, Columbia University: *Sequential Analysis of Statistical Data: Applications*, rev. ed., Columbia University Press, New York, 1945.
- THOMPSON, CATHERINE M.: "Table of Percentage Points of the χ^2 Distribution," *Biometrika*, Vol. 32 (1941), pp. 187-191.
- TIPFETT, L. H. C.: *Random Sampling Numbers*, Cambridge University Press, London, 1927.
- WALD, A.: "Tests of Statistical Hypotheses concerning Several Parameters When the Number of Observations Is Large," *Transactions of the American Mathematical Society*, Vol. 54 (1943), pp. 426-482.
- : "Sequential Tests of Statistical Hypotheses," *Annals of Mathematical Statistics*, Vol. 16 (1945), pp. 117-186. Reprints available from Institute of Mathematical Statistics, 116 Rackham Hall, Ann Arbor, Mich.
- WALLIS, W. ALLEN: "Compounding Probabilities from Independent Significance Tests," *Econometrica*, Vol. 10 (1942), pp. 229-248.
- WILKS, S. S.: "Certain Generalizations in the Analysis of Variance," *Biometrika*, Vol. 24 (1932), pp. 471-494.

CHAPTER 4

EFFECTS OF ROUNDING OR GROUPING DATA

	PAGE
1. Introduction	187
2. Rounded Numbers and Scale Readings	188
3. The Rounding Rule and Its Properties	189
4. Effects of Rounding on Statistical Analyses of Large Numbers of Observations	191
4.1 Nature of the Effects	191
4.2 Sheppard's Corrections	193
4.3 Comparison of the Distribution of the Mean of N Rounded Observations and the Distribution of the Mean of N Unrounded Observations, When N is Large	196
4.4 Comparison of the Distributions of s^2 for Rounded and Unrounded Observations, When the Number of Observations is Large	198
4.5 Effect of Rounding on the Distribution of Student's t	200
5. Effects of Rounding on Statistical Analyses of Small Numbers of Observations from a Normal Population.	203
5.1 Introduction	203
5.2 Exact Distributions of s_{xR}^2 in Samples of 2 and 3 from a Normal Population	203
5.2.1 Illustrative Distributions	203
5.2.2 Effect of the Position of the Rounding Lattice.	206
5.3 Combinations of Sample Sizes and Rounding-interval Widths for Which the Actual Distribution of s_{xR}^2 Can Be Approximated Satisfactorily by a Continuous Distribution, When the Sampling Is from a Normal Population.	213
5.4 Distribution of Student's t and the Variance Ratio When Based on a Small Number of Rounded Observations	214
6. Statistical Properties of Tabular and Interpolated Values	215
7. References	222

FIGURES

4.1 Distribution of s_{xR}^2 for Samples of 2 from a Normal Population When the Width of the Rounding Interval Is One Standard Deviation, and Cor- responding Continuous Distributions of s_x^2 and $s_x'^2 \approx (1\frac{3}{12})s_x^2$	204
4.2 Distribution of s_{xR}^2 for Samples of 2 from a Normal Population When the Width of the Rounding Interval Is One-half Standard Deviation, and Corresponding Continuous Distribution of s_x^2	205
4.3 Distribution of s_{xR}^2 for Samples of 2 from a Normal Population When the Width of the Rounding Interval Is One-quarter Standard Deviation, and Corresponding Continuous Distribution of s_x^2	206
4.4 Distribution of s_{xR}^2 for Samples of 3 from a Normal Population When the Width of the Rounding Interval Is One Standard Deviation, and Cor- responding Continuous Distribution of s_x^2	207

men may have the same height when measured by inches, yet the finer the measurements the more seldom will they be identical, till finally the chance that four men will have *exactly* the same height is infinitely small. If we had smaller grouping the zero values of the standard deviation might be expected to increase, and a similar consideration will show that the smaller values of the standard deviation would also be likely to increase, such as 0.436, when 3 fall in one group and 1 in an adjacent group, or 0.50 when 2 fall in two adjacent groups. On the other hand, when the individuals of the sample lie far apart, the argument of Sheppard's correction will apply, the real value of the standard deviation being more likely to be smaller than that found owing to the frequency in any group being greater on the side nearer the mode.

These two effects of grouping will tend to neutralize each other in their effect on the mean value of the standard deviation but both will increase the variability.

Accordingly, we find that the mean value of the standard deviation is quite close to that calculated, while in each case the variability is sensibly greater. The fit of the curve is not good, both for this reason and because the frequency is not evenly distributed owing to effects (2) and (3) of grouping. On the other hand, the fit of the curve giving the frequency of z is very good, and as that is the only practical point the comparison may be considered satisfactory.

The Statistical Research Group received various sets of data that exhibited curious statistical properties. In some instances it was found that these properties were attributable to the coarse rounding employed in recording the data. In at least one instance the peculiarities were attributable to the fact that a fraction of the data had been recorded with half the precision of the remainder, owing (in part) to intrinsic differences in the precisions of the two machines used to obtain the measurements. Occasionally the Group was asked to make recommendations with regard to the recording of data, since its investigations had shown that in many cases the trouble arose in connection with recording the data and not in the actual reading of the scales. As a consequence of difficulties encountered in analysing coarsely rounded data and of requests for advice on rounding in general, a study of rounding was undertaken, principally from the viewpoint of its effect on the standard procedures of statistical analysis. The results of this study are summarized in this chapter. Much of the material presented here can be found in the literature of statistics, but it is widely scattered.

2. ROUNDED NUMBERS AND SCALE READINGS

Rounded numbers enter the practical man's world through two different doorways. First, the measurements of a scientist or engineer are rounded numbers, since all measuring equipment is of limited accuracy. Second, data are often recorded to less accuracy than is attainable with the available equipment, the accuracy preserved being more easily

tion mean, divided by the standard deviation of the sample, the latter defined as above (see Sec. 4.4 below).

attained and "adequate for the purposes at hand"; or they are rounded in computing, sometimes to simplify arithmetical calculations, as when 0.40 is used in place of $51/128$ (0.3984375 is exact), and sometimes because it cannot be avoided, as when 3.1416 is used in place of π .*

In the case of the computer's reduction of exact numbers to rounded numbers in decimal form, assuming that he has rounded them correctly in accordance with the rule given in the next section, it can be stated that each is accurate within $\frac{1}{2}$ unit in the last decimal place retained. In the case of the scientist's or the engineer's measurements this may not be true, and yet the last figures retained may contain worth-while information, in the sense that when the last figures are retained the data are more accurate than when the last figures are omitted entirely or are used as a basis for rounding the results to one less place. In such cases, if the measurements are all of comparable accuracy, there will exist a "unit" of measurement, with respect to which the uncertainty of a given measurement is $\frac{1}{2}$ a unit.

Consider, for example, the case of an experimenter taking "readings" on a scale with graduations every $\frac{1}{8}$ in. He can read his determination to the nearest $\frac{1}{8}$ in. directly and may then visually estimate it to the nearest $\frac{1}{16}$ in., obtaining, say, a reading of $3\frac{7}{16}$ in. If he writes this out in decimal form it becomes 3.4375 in., and represents some number between 3.40625 in. ($3\frac{13}{32}$ in.) and 3.46875 in. ($3\frac{15}{32}$ in.), and this is accurate only to within ± 0.03125 in. and not to within 0.00005 in., as the number of decimal places retained might suggest. He may decide, therefore, to report the value as 3.44, which is accurate only to within ± 0.02875 and -0.03375 , but which will be closer to the true value than is 3.4, unless the true value lies between 3.40625 and 3.42000. When so reported, however, his readings will not give a clear indication of their accuracy. If an unambiguous indication of their accuracy is important, he should report his readings in units of $\frac{1}{8}$ in., in which event they will be accurate to within plus or minus $\frac{1}{2}$ unit.

3. THE ROUNDING RULE AND ITS PROPERTIES

When a number expressed in the decimal system is to be rounded to a specific number of significant figures,† the rounding should always be carried out in accordance with the following rule:

* The mathematician has devised convenient symbols for certain very practical quantities, such as the diagonal of a square of unit side ($\sqrt{2}$) and the ratio of the circumference of a circle to its diameter (π), which cannot be expressed *exactly* as common fractions or as decimal numbers with a finite number of decimals. By using the mathematician's symbols for these quantities, the practical man can usually keep his algebraic manipulations simple, but sooner or later there comes a point at which a numerical answer is needed, and here it becomes necessary to replace π (3.14159 26535 89793 23846+) with a common fraction, such as $355/113$ (which is correct to 6 decimal places), or with a decimal approximation such as 3.141593.

† A *significant figure* of a number (expressed in the decimal system of notation)

Rounding Rule:

a. If the first digit to be dropped is less than 5, the last digit retained shall be left unchanged.

b. If the first digit to be dropped is greater than 5, or is a 5 followed by digits greater than 0, the last digit retained shall be increased by 1.

c. If the first digit to be dropped is a 5 alone, or a 5 followed by 0's only, the last digit retained shall be rounded to the nearest even number. Thus, rounding to 2 decimal places,

$$\pi \doteq 3.141593 \text{ yields } 3.14$$

$$e \doteq 2.718282 \text{ yields } 2.72$$

$$1/22 \doteq 0.045455 \text{ yields } 0.05$$

$$1/200 \doteq 0.005000 \text{ yields } 0.00$$

$$1/198 \doteq 0.005051 \text{ yields } 0.01$$

$$10/2,247 \doteq 0.004450 \text{ yields } 0.00$$

It is clear that to every number that is to be "rounded down" in accordance with part (a) of the rule there corresponds a number that is to be "rounded up" in accordance with part (b). Parts (a) and (b) thus establish a balance between rounding down and rounding up for all numbers other than those that are exactly 5 in the first place to be dropped. Part (c) establishes a similar balance between rounding down and rounding up for numbers that are exactly 5 in the first place to be dropped, by specifying that the rounding shall be up when the preceding digit is 1, 3, 5, 7, and 9; down, when it is 0, 2, 4, 6, 8. Part (c) is arbitrary, since rounding to the nearest odd number would establish a balance in these cases equally well, being equivalent to merely interchanging the words up and down in the preceding sentence. However, uniformity of procedure is important for checking, and consistency of published tables is desirable, so part (c), being well established, should be adhered to.

A question that arises naturally at this point is: Will repeated applications of the rule (dropping digits singly, or in pairs, or otherwise) always lead to the same result, when the rounding is stopped at a specified place, as a single rounding to that place? The answer, unfortunately, is No. The fifth example in the list above is a case in point. If 0.005051 is rounded to 2 decimal places in accordance with the rule in almost any manner involving more than one step, the result is 0.00, which is "incorrect." The third example may be used to illustrate the fact that the number of places to which a number is originally tabulated may affect the outcome of subsequent rounding: $1/22 = 0.045454545 \text{ ad infinitum}$;

is any digit that contributes to the specification of the magnitude of the number aside from serving to locate the decimal point. For example, 345 and 0.000345 each have three significant figures; 34.05 and 34.50 (as distinct from 34.5) each have four significant figures; 34500 has 3, 4, or 5 according as it means 3.45×10^5 , 3.450×10^5 , or 3.4500×10^5 , respectively.

correct to 6 decimal places it equals 0.045 455, the value given in the table above; if this latter value is rounded to 5 decimals in accordance with the rule, the result is 0.045 46; however $\frac{1}{2}_2$ equals 0.045 45 correct to 5 decimals, the result that will be obtained by rounding to 5 decimals when the value originally tabulated is correct to 7 decimals or more.

It is clear from the foregoing that, when an n -place table is prepared by rounding the entries given in an $(n + k)$ -place table, some of the entries may not be correct in the n th place. Thus, in a table of $\log_e N$ to 5 decimal places, the 5-place value given for $\log_e 1947 = 7.57404\ 50054$ will be incorrect in the fifth place if obtained by rounding from less than an 8-place table with entries correct in the eighth place. Final 5's can, however, be marked to show whether further rounding should be up or down; see, for example, Tables 1.1 and 1.5 of Chap. 1, in which each final 5 is italicized if rounding should not be in accordance with part (c) of the rule.

It may be asked whether there exists a rounding rule that will always lead to the same result at a specified place, irrespective of the number of applications of the rule employed in rounding to that place. A procedure suggested by Cayley* possesses this advantage. According to this procedure, the figure in the last place to be retained is not adjusted at all—which is equivalent to rounding down irrespective of the digits that follow—with the result that the number recorded either is exact or errs in defect. If, when a recorded number of this type is used, a final 5 is affixed to it, then the error will lie between plus and minus $\frac{1}{2}$ unit in the last place recorded, as is the case when the number recorded is rounded in a single step from its exact value in accordance with the Rounding Rule. For example, π would be recorded to 4 decimals as 3.1415, and would be taken to be 3.14155 in further calculations. Whereas Cayley's procedure has the advantages that it is simple (since numbers are always rounded down), that it can be mechanized for purposes of machine computation, and that it yields an n -place recorded number that is independent of the number of rounding steps involved in reaching it from the exact value, it has the disadvantage that it requires the use of $(n + 1)$ -place numbers in further computations in order to attain the same degree of accuracy that would be obtained by using n -place numbers rounded in accordance with the Rounding Rule.

4. EFFECTS OF ROUNDING ON STATISTICAL ANALYSES OF LARGE NUMBERS OF OBSERVATIONS

4.1. Nature of the Effects

Frequently a statistician analyzes measurements recorded to several decimal places more than can possibly have any practical significance.

* CAYLEY, letter to J. W. L. Glaisher.

The extra decimal places do not occasion any great concern, for nothing has been done that cannot be undone. Recording the extra digits and rounding the measurements are merely unnecessary nuisances. On the other hand, measurements are sometimes recorded to the nearest 5, 10, 20, 50, or 100 units, or still more coarsely, when they could, and should, have been recorded to the nearest unit, or even more accurately. Thus, if duplicate measurements taken under essentially the same conditions tend to differ on the average by about 50 units, research workers often record the measurements to the nearest 10 or 20 units; sometimes only to the nearest 50 units. If measurements taken under essentially the same conditions tend to be distributed approximately normally about a "true value" with a standard deviation of σ , these roundings correspond to intervals with widths roughly 0.23σ , 0.45σ , and 1.1σ , respectively.* Statisticians, on the other hand, recommend that the width of the rounding interval be less than one-third, or, better, less than one-fourth the standard deviation of random sampling.†

Basically, the choice of the size of a rounding or grouping interval depends on the answers to the following three questions:—

a. If the observations x_1, x_2, \dots, x_N are to be regarded as independent values of a random variable x , which, in the population from which the data are drawn, is distributed about a mean of μ with a standard deviation σ , then what is the effect of the rounding (grouping) on the sample estimates of μ and σ , defined by

$$\bar{x} = \frac{\sum_{i=1}^N x_i}{N} \quad (1)$$

and

$$s = \sqrt{\frac{\sum_{i=1}^N (x_i - \bar{x})^2}{N - 1}} \quad (2)$$

b. What is the effect of the rounding on confidence limits for μ and σ based on \bar{x} and s ?

c. What is the effect of the rounding on statistical tests of hypotheses about μ and σ based on \bar{x} and s ?

In the present section, answers to these questions will be given for the case when the number of observations N is large. In Sec. 5 the case where N is small, perhaps only 2 or 3, is discussed; the results given there

* The average difference between duplicate measurements is, under the assumptions stated, $2\sigma/\sqrt{\pi} = 1.12838\sigma$. If this average difference is 50, a grouping interval of 10 corresponds with $1.12838\sigma/5 = 0.226\sigma$, and similarly for a grouping interval of 20.

† See, for example, FISHER, *Statistical Methods*, Sec. 13.

throw light on what values of N may be regarded as large and what values must be regarded as small.

4.2. Sheppard's Corrections

In order to answer the first question, consider the relation between the k th (population) moment

$$\mu'_k = E(x^k) = \int_{-\infty}^{+\infty} x^k p(x) dx \quad (k = 1, 2, 3, 4, \dots) \quad (3)$$

of a continuous random variable distributed according to the probability density function* $p(x)$, and the k th moment

$$\nu'_k = \sum_{i=-\infty}^{+\infty} x_i^k \int_{x_i - \frac{w}{2}}^{x_i + \frac{w}{2}} p(t) dt \quad (k = 1, 2, 3, 4, \dots) \quad (4)$$

of the histogram formed by grouping the values of x into classes of width w with mid-points x_i ($i = 0, \pm 1, \pm 2, \dots$). The μ'_k are, by definition, the moments (about the origin) of x in the population, in which x is a continuous variable. On the other hand, since it is not possible either to read or to record with perfect accuracy all values of a continuous variable, recorded values of x will generally be rounded values, any value of x between $x_i - (w/2)$ and $x_i + (w/2)$ being recorded as x_i . Hence, in a sense, the ν'_k are *realistic* moments of x and the μ'_k are *ideal* moments.

If, first, $p(x)$ can be expanded in a Taylor series throughout the range for which $p(x) > 0$, second, $x^k p^{(2n)}(x)$ is finite and continuous throughout this range ($k = 1, 2, 3, 4, \dots$; $n = 1, 2, 3, 4, \dots$), and third, $p(x)$ and $p^{(n)}(x)$ ($n = 1, 2, \dots$) vanish at the limits of this range, then the ν'_k and the μ'_k are related as follows:

$$\begin{aligned} \nu'_1 &= \mu'_1 \\ \nu'_2 &= \mu'_2 + \frac{w^2}{12} \\ \nu'_3 &= \mu'_3 + \left(\frac{w^2}{4}\right) \mu'_1 \\ \nu'_4 &= \mu'_4 + \left(\frac{w^2}{2}\right) \mu'_2 + \frac{w^4}{80} \\ &\dots \dots \dots \\ \nu'_k &= \sum_{i=0}^{\infty} \left[C_{2i}^k \left(\frac{w}{2}\right)^{2i} (2i+1) \right] \mu'_{k-2i} \end{aligned} \quad (5)$$

where $C_r^k = k!/[r!(k-r)!]$ for $0 \leq r \leq k$, and $C_r^k = 0$ for $r > k$.†

* That is, for any value of c , the integral $P(c) = \int_{-\infty}^c p(x) dx$ equals the probability that x is less than c , $0 \leq P(c) \leq 1$ for all values of c , $P(-\infty) = 0$, and $P(+\infty) = 1$.

† SHEPPARD, "Most Probable Values of Frequency Constants." The corresponding case of two variables has been considered by Baten, "Corrections for the Moments," and of several variables by Wold, "Sheppard's Correction Formulae."

The three conditions regarding $p(x)$ imply that it is not only continuous over the range for which $p(x) > 0$ but tapers off strongly to zero at the ends of this range; they thus exclude probability curves with abrupt ends, such as a uniform distribution over $-w/2$ to $+w/2$, and U -shaped or J -shaped curves. The three conditions are necessary and sufficient for the relations (5) to hold exactly. Relations analogous to (5), with additional terms, have been obtained for cases excluded by the above assumptions.*

The relations (5) can be derived in a somewhat more general manner that shows that they are valid *on the average* whenever the moments involved exist, provided that the rounding lattice is imposed at random on the underlying distribution.† Suppose the x axis is first divided in a definite manner into an infinite number of class intervals of width w/m , where m is some integer greater than 1. Given a probability density function $p(x)$, the histogram corresponding to this grouping of the values of x can always be determined from

$$p(x_j) = \int_{x_j - \frac{w}{2m}}^{x_j + \frac{w}{2m}} p(t) dt \quad (j = 0, \pm 1, \pm 2, \dots) \quad (6)$$

where x_j is the mid-point of the j th subdivision, since the integrals involved will always exist when $p(x)$ is a probability density function. The moments about the origin of this basic histogram, μ_k'' , say, can be determined from the summation analogous to (4), so far as they exist (that is, are finite). Corresponding to the basic histogram determined by (6), m new histograms can be formed by combining the successive subclasses of width w/m into subclasses of width w , the intervals containing x_0, x_1, \dots, x_{m-1} being combined in one instance, the intervals containing x_1, x_2, \dots, x_m being combined in the next instance, and so forth. Corresponding to each of these histograms, moments about the origin, $\nu_k'(s)$, $s = 1, 2, \dots, m$, can be determined from summations analogous to (4), so far as they exist. Let $\bar{\nu}_k'$ denote the average of the values of $\nu_k'(s)$, $s = 1, 2, \dots, m$, then the $\bar{\nu}_k'$ and the μ_k'' are related as follows, in so far as they exist:

$$\begin{aligned} \bar{\nu}_1' &= \mu_1'' \\ \bar{\nu}_2' &= \mu_2'' + \left[1 - \frac{1}{m^2}\right] \cdot \frac{w^2}{12} \\ \bar{\nu}_3' &= \mu_3'' + \left[1 - \frac{1}{m^2}\right] \cdot \frac{w^2}{4} \cdot \mu_1'' \\ \bar{\nu}_4' &= \mu_4'' + \left[1 - \frac{1}{m^2}\right] \cdot \frac{w^2}{2} \cdot \mu_2'' + \left[1 - \frac{1}{m^2}\right] \cdot \left[3 - \frac{7}{m^2}\right] \cdot \frac{w^4}{240} \end{aligned} \quad (7)$$

* See papers by Elderton, Pairman and Pearson, Pearse, and Pearson listed in Sec. 7 below.

† See the papers by Abernathy, Craig, and Carver listed in Sec. 7.

and so forth. Letting $m \rightarrow \infty$, the right-hand sides of these equations tend to the corresponding expressions in equations (5), since $\mu_k'' \rightarrow \mu_k'$ as $m \rightarrow \infty$. On the other hand, the $\bar{\nu}_k'$ retain their meanings as average values of the ν_k' . Accordingly, whatever the nature of the distribution of x , equations (5) hold *on the average*, that is, they give the average relationships between the ν_k' and the μ_k' , provided these are finite, for an infinite series of trials in which a rounding lattice composed of sections of width w is imposed at random on the underlying probability distribution.

The results given above all refer to moments about a fixed point taken as the origin, and the values of the moments involved will depend upon the choice of the origin. Thus, if x denotes temperature and is measured in degrees Fahrenheit, the values of the μ_k' and ν_k' will be different from those obtained when x is measured in degrees centigrade. The results obtained will be the same, however, if the origin is chosen at the mean of the distribution of x . Dropping the primes to signify moments about the mean of x , relations (5) correspond with

$$\begin{aligned}\nu_1 &= \mu_1 = 0 \\ \nu_2 &= \mu_2 + \frac{w^2}{12} \\ \nu_3 &= \mu_3 \\ \nu_4 &= \mu_4 + \frac{w^2}{2} \cdot \mu_2 + \frac{w^4}{80}\end{aligned}\tag{8}$$

and so forth.

Comparison of the second equation of (8) with (22) shows that the variance (second moment about the mean) of a rounded value of x , which may be denoted by x_R for convenience, equals the variance of x , namely μ_2 , plus a variance $w^2/12$, which equals the variance of a rounding error ϵ , which is distributed uniformly between $-w/2$ and $+w/2$. This suggests that we may write

$$x_R = x + \epsilon\tag{9}$$

where x_R denotes a value of x rounded to within $\pm w/2$, and ϵ is a random variable independently distributed with uniform probability density between $-w/2$ and $+w/2$. That the representation (9) is strictly valid under the three conditions stated above, and that it is valid *on the average*, in the above sense, under any conditions for which the moments exist, has been demonstrated rigorously.*

Since it is usually desired to determine the μ_k from the ν_k , equations (8) are customarily solved for the μ_k in terms of the ν_k and powers of w , and the relations given as

* See papers by Craig and by Langdon and Ore, listed in Sec. 7.

$$\begin{aligned}
 \mu_1 &= \nu_1 = 0 \\
 \mu_2 &= \nu_2 - \frac{w^2}{12} \\
 \mu_3 &= \nu_3 \\
 \mu_4 &= \nu_4 - \frac{w^2}{2} \cdot \nu_2 + \frac{7w^4}{240} \\
 &\text{and so forth.}^*
 \end{aligned} \tag{10}$$

These adjustments of the ν_k to obtain the μ_k are customarily called Sheppard's corrections for grouping. As has been indicated above, they are valid as average adjustments whenever the moments involved exist, provided that the rounding lattice is imposed *at random* on the underlying distribution. This latter provision means, for example, that when values of a variable that can take only nonnegative values are to be rounded, zero shall not inevitably be adopted as the lower extremity of the lowest class—indeed, the mid-point of the lowest class may turn out to be a small negative number. If the rounding lattice is not imposed at random when Sheppard's original assumptions are not fulfilled, then the foregoing adjustments may be wildly wrong and may even adjust in the wrong direction.†

4.3. Comparison of the Distribution of the Mean of N Rounded Observations and the Distribution of the Mean of N Unrounded Observations, When N Is Large

Sheppard's corrections make possible a concise comparison of the distribution of the mean of N rounded observations and the distribution of the mean of N unrounded observations, when N is large. Continuing the notation adopted in connection with (9), let

$$\bar{x}_R = \sum_{i=1}^N \frac{x_{Ri}}{N} \tag{11}$$

where x_{Ri} is the rounded value of x_i , the i th of N independent values of a random variable x , corresponding to a rounding lattice with classes of

* The corresponding relations for μ_5 to μ_8 are given in Rietz, *Handbook*, p. 94. They can be obtained by letting $m \rightarrow \infty$ in the expressions for μ_5 to μ_8 given by Craig. Letting λ_k and L_k ($k = 1, 2, \dots$) denote the semi-invariants of the unrounded variable x and the rounded variable x_R , respectively, the corresponding relations become simply

$$\begin{aligned}
 \lambda_{2m} &= L_{2m} + (-1)^m B_m \frac{w^{2m}}{2m} \\
 \lambda_{2m+1} &= L_{2m+1}
 \end{aligned}$$

where B_m is the m th Bernoulli number. Thus, $\lambda_4 = L_4 + w^4/120$, $\lambda_6 = L_6 - w^6/252$, $\lambda_8 = L_8 + w^8/240$, and so forth. For further details, see the papers by Craig, Langdon and Ore, and Wold.

† The reader who wishes to delve further into the mathematical background of Sheppard's corrections is urged to read Kendall's paper.

width w (located at random on the x axis, if Sheppard's assumptions are not fulfilled). Furthermore, let

$$\begin{aligned} \text{the mean of } x \text{ in the population} &= \mu'_{1;x} \\ \text{the variance of } x \text{ in the population} &= \sigma_x^2 = \mu_{2;x} \quad (12) \\ \text{the } k\text{th moment of } x \text{ about its population mean} &= \mu_{k;x} \\ &\quad (k = 1, 2, \dots) \end{aligned}$$

and let

$$w = a \cdot \sigma_x \quad (13)$$

Table 4.1 presents a comparison of the distribution of \bar{x}_R in regard to mean, variance, skewness, and kurtosis with the distribution of x and with a normal distribution of mean μ'_1 and variance σ^2 .

From a study of Table 4.1 it is apparent that

(1) \bar{x} and \bar{x}_R are each unbiased estimators of the population mean of x .

(2) The variance of \bar{x}_R is $(1 + a^2/12)$ times the variance of \bar{x} .

(3) The skewness ($\gamma_1 = +\sqrt{\beta_1}$ of Pearson's notation) of the distribution of \bar{x}_R never exceeds that of the distribution of \bar{x} .

(4) The kurtosis ($\gamma_2 = \beta_2 - 3$ of Pearson's notation) of the distribution of \bar{x}_R is always less than that of the distribution of \bar{x} .

(5) When N is large, \bar{x} and \bar{x}_R are approximately normally distributed about the population mean of x , $\mu'_{1;x}$.

The case in which the ungrouped variable x is normally distributed is of special interest. In this case \bar{x} is likewise normally distributed, whereas the distribution of \bar{x}_R is symmetric but has slightly less kurtosis than a normal distribution, the deficiency being $(a^4/120N)/(1 + a^2/12)^2$. From the Gram-Charlier series for the "generalized normal curve,"* it is seen that this deficiency in kurtosis implies that the distribution of \bar{x}_R has slightly less area in the "central region," say, between $\pm 0.75\sigma_{\bar{x}_R}$, slightly less also in the "tails," say, beyond $\pm 2.3\sigma_{\bar{x}_R}$, and slightly more between these points. For any practical rounding, say, $a = w/\sigma < 1$, this effect will surely be negligible. R. A. Fisher has shown† that the maximum likelihood estimate $\hat{\mu}$ of $\mu'_{1;x}$ from N independent rounded values x_R of a normally distributed variable x has a variance of $(1 + a^2/12 - a^6/2,880 + \dots) \cdot \sigma_x^2/N$. The loss of precision when \bar{x}_R is used instead of μ is, therefore, only $a^6/2,880$, which is clearly negligible for any practical rounding.

In conclusion

a. \bar{x}_R is an unbiased estimator of the population mean of x , $\mu'_{1;x}$, whatever the value of N .

b. When N is large and the values of σ_x^2 and w are known, so that $\sigma_{\bar{x}_R}^2 = (\sigma_x^2 + w^2/12)/N$ can be evaluated, confidence limits for, and

* See, for instance, RIETZ, *Handbook*, p. 114.

† FISHER, "Mathematical Foundations," p. 362.

statistical tests of hypotheses regarding the value of $\mu'_{1:x}$ carried out with $(\bar{x}_R - \mu'_{1:x})/\sigma_{\bar{x}_R}$ regarded as a normal deviate will be approximately correct—provided the true distribution of x has “high order contact” (that is, Sheppard’s assumptions are valid), or the rounding lattice is located at random with respect to the admissible values of x , or both.

TABLE 4.1

COMPARISON OF THE MEAN, VARIANCE, SKEWNESS, AND KURTOSIS OF THE DISTRIBUTION OF THE AVERAGE OF N INDEPENDENT ROUNDED VALUES OF A RANDOM VARIABLE WITH THE CORRESPONDING CHARACTERISTICS OF THE DISTRIBUTION OF THE UNROUNDED VARIABLE AND OF A NORMAL (GAUSSIAN) DISTRIBUTION WHEN THE WIDTH OF THE ROUNDING INTERVAL IS a STANDARD DEVIATION UNITS ($w = a \cdot \sigma$)

Characteristic	Distribution		
	Unrounded variable, x	Average of N rounded values, \bar{x}_R	Normal
Mean	$\mu'_{1:x}$	$\mu'_{1:\bar{x}}$	μ'_1
Variance	σ_x^2	$\frac{\left(1 + \frac{a^2}{12}\right) \sigma_x^2}{N}$	σ^2
Skewness (γ_1)	$\gamma_{1:x} = \frac{\mu_{3:x}}{\sigma_x^3}$	$\frac{\gamma_{1:\bar{x}}}{\sqrt{N \left(1 + \frac{a^2}{12}\right)^3}}$	0
Kurtosis (γ_2)	$\gamma_{2:x} = \frac{\mu_{4:x}}{\sigma_x^4} - 3$	$\frac{\gamma_{2:\bar{x}} - \frac{a^4}{120}}{N \left(1 + \frac{a^2}{12}\right)^2}$	0

4.4. Comparison of the Distribution of s^2 for Rounded and Unrounded Observations, When the Number of Observations Is Large

Let

$$s_{\bar{x}_R}^2 = \sum_{i=1}^N \frac{(x_{Ri} - \bar{x}_R)^2}{N-1} \quad (14)$$

where x_{Ri} ($i = 1, 2, \dots, N$) and \bar{x}_R are as in (11). In Table 4.2 the mean of $s_{\bar{x}_R}^2$ and the ratio of the variance of $s_{\bar{x}_R}^2$ to the square of its mean are compared with the mean and corresponding ratio for s_x^2 under two sets of conditions: first, when x has any distribution for which the first four moments exist; second, when x is normally distributed.

It is evident from a study of Table 4.2 that the ratio

$$(\text{variance of } s^2)/(\text{mean of } s^2)^2$$

is always less in the case of $s_{x_R}^2$ than in the case of s_x^2 . The difference is slight, however, and for any reasonable rounding, say, $a = w/\sigma < 1$, will generally be negligible. Therefore

(1) When N is large, $(N-1)s_{x_R}^2/(\sigma_x^2 + w^2/12)$ and $(N-1)s_x^2/\sigma_x^2$ will be distributed as χ^2 with $N-1$ degrees of freedom to about the same order of approximation.

TABLE 4.2

THE MEAN OF $s_{x_R}^2$ AND OF THE RATIO OF THE VARIANCE OF $s_{x_R}^2$ TO THE SQUARE OF THE MEAN COMPARED WITH THE CORRESPONDING QUANTITIES FOR s_x^2 , WHEN THE DISTRIBUTION OF x IS ARBITRARY* AND WHEN THE DISTRIBUTION OF x IS NORMAL

$\left(a = \frac{w}{\sigma_x}\right)$			
Distribution of x	Arbitrary		Normal
Statistic	s_x^2	$s_{x_R}^2$	s_x^2
Mean	σ_x^2	$\left(1 + \frac{a^2}{12}\right) \cdot \sigma_x^2$	σ_x^2
Variance (Mean) ²	$\frac{2}{N-1} + \frac{\gamma_{2;x}}{N}$	$\frac{2}{N-1} + \frac{\gamma_{2;x} - \frac{a^4}{120}}{N}$	$\frac{2}{N-1}$

* Subject to the restriction that the first four moments of x about its population mean exist.

(2) The quantity $s_{x_R}^2 - w^2/12$ is an unbiased estimator of the variance of x in the population σ_x^2 , whatever the value of N , provided the distribution of x has high order contact (that is, Sheppard's three assumptions, stated in Sec. 4.2, are fulfilled), or the rounding lattice is located at random with respect to the admissible values of x , or both.*

It may be well to point out here that the ratio

$$(N-1)(s_{x_R}^2 - w^2/12)/\sigma_x^2$$

should not be used as a substitute for the ratio given in (1) unless $a = w/\sigma$ is quite small, since the variance of this ratio exceeds the variance of the ratio given in (1) by a factor of $(1 + a^2/12)^2$, which will generally render

* When N is small, the mean and variance/(mean)² relations shown in Table 4.2 are still valid, but the discontinuities of the distribution of $s_{x_R}^2$ are such that graduation of the distribution of $s_{x_R}^2$ by a continuous distribution is virtually impossible (see Sec. 5.1).

Kendall has remarked that (2) gives the correct estimator of σ_x^2 if the rounding of the values of x is determined before the sample is drawn. If, on the other hand, the observations x_1, x_2, \dots, x_N are drawn first and then rounded, he suggests that $s_{x_R}^2 - w^2/(12(N-1))$ be used to estimate σ_x^2 . When N is large the difference is clearly negligible from a practical standpoint but is of some theoretical interest.

the χ^2 approximation less accurate. If the adjusted numerator and the denominator $\sigma_x^2 + w^2/12$ are used, then the variance of the resulting ratio will be the same as the variance of the ratio given in (1), but the mean will be deficient by a factor of $1/(1 + a^2/12)$. If $s_{x_R}^2$ is used in the numerator and σ_x^2 in the denominator, the mean will be excessive by a factor of $(1 + a^2/12)$ and the variance by a factor of $(1 + a^2/12)^2$. Consequently,

(3) Determinations of confidence limits for, and statistical tests of hypotheses regarding, the value of σ_x^2 should be based on $s_{x_R}^2$ as implied by (1) and will be valid to the extent that the conditions and approximations thereof obtain.

In conclusion, it should be remarked that the foregoing discussion can be carried over to the case where $s_{x_R}^2$ has been obtained from an analysis of variance of values of x that have been rounded to within $\pm w/2$ and has n degrees of freedom. The only change required is replacement of $N - 1$ by n throughout.

4.5. Effect of Rounding on the Distribution of Student's t

Let

$$t_z = \frac{\sqrt{N}(\bar{x} - \mu'_{1;z})}{s_z} \quad (15)$$

and

$$t_{x_R} = \frac{\sqrt{N}(\bar{x}_R - \mu'_{1;x})}{s_{x_R}} \quad (16)$$

where \bar{x} and \bar{x}_R are as in (1) and (11), s_z and s_{x_R} are as in (2) and (14), $\mu'_{1;x}$ is the mean value of x in the population, and N is the number of independent values of x (or of x_R) in the sample.

When the N independent observations involved are from a normal distribution, the distribution of t_z is known as "Student's t distribution," in recognition of the fact that the distribution of $z = t/\sqrt{N - 1}$ under these conditions was first given by Student in the epochal paper from which the quotation in Sec. 1 of this chapter is taken. In his derivation, Student utilized the independence of \bar{x} and s when computed from independent observations from a normal population, although he himself merely established the fact that the product moment coefficients of correlation between \bar{x} and s , and between \bar{x}^2 and s^2 , are zero under these conditions. Independence of \bar{x} and s is actually a necessary condition. A rigorous proof of their independence in random samples from a normal population was communicated to Student by R. A. Fisher in correspondence prior to the First World War; this first saw light, only incidentally, as a preliminary step in Fisher's paper, published in 1915, on the exact sampling distribution of the correlation coefficient.* The first complete

* FISHER, "Distribution of the Correlation Coefficient."

derivation of Student's distribution was given, in terms of t , by Fisher in 1926,* although he had given a more general definition of t two years earlier.†

As Student pointed out in the passage quoted in Sec. 1 of this chapter, there is a correlation between the sample mean and the sample standard deviation in random samples of rounded observations, resulting from the rounding, so that \bar{x}_R and s_{x_R} will not be independently distributed even when \bar{x} and s_x are independent. Nevertheless, Student's experimental results suggest that the distribution of t_{x_R} will closely approximate that of t_x when N is large enough to render negligible the discontinuities of the distribution of t_{x_R} . That this is so is evident from a study of the first four moments of t_{x_R} for the case of x having an arbitrary distribution subject only to the condition that its first four moments exist. The first four moments of t_{x_R} can be evaluated readily, under this assumption regarding x , from the expressions for the first four moments of t in terms of the semi-invariants of x , given by Geary.‡ The first four moments of t_{x_R} are given in Table 4.3, where they are compared with the first four moments of Student's t distribution, that is, the moments of t_x when x is normally distributed.§

It is evident from a study of Table 4.3 that, to terms of order $1/N$, rounding affects only the fourth moment, and that the effect is clearly negligible in the case of samples from a normal population ($\gamma_{1;x} = 0$ and $\gamma_{2;x} = 0$) for any reasonable rounding, say, $a = w/\sigma < 1$. It can be seen from a study of Geary's more extensive formulas that, when the distribution of x is symmetrical but not necessarily normal, the first and third moments of t_{x_R} are zero through terms in $1/N^2$ at least and the variance of t_{x_R} has its normal value through the terms in $1/N$. Indeed, when x is normally distributed, the variance of t_{x_R} has its normal value through terms in $1/N^2$ also. Therefore, it may be stated that

When N is sufficiently large and w is sufficiently small to render the discontinuities of the distribution of t_{x_R} negligible, the distribution of t_{x_R} and t_x will follow the standard t distribution to about the same order of approximation, provided the distribution of x has high order contact, or the rounding lattice is located at random with respect to the admissible values of x , or both.

* FISHER, "Applications of Student's Distribution."

† FISHER, "Error Function of Well-Known Statistics."

‡ GEARY, "Distribution of Student's Ratio."

§ The moments of t_{x_R} are given to terms of order $1/N$; that is, terms in the $\frac{3}{2}$ and higher powers of $1/N$ have been neglected. Geary's general expressions for the first four moments are correct to terms of order $1/N^2$. The terms of order $1/N^{3/2}$ and $1/N^2$ for t_{x_R} can be evaluated with the aid of the semi-invariants of x_R given in the footnote to expressions (10) above.

TABLE 4.3
 FIRST FOUR MOMENTS OF THE DISTRIBUTION OF STUDENT'S t WHEN t IS BASED ON A SAMPLE OF N INDEPENDENT ROUNDED OBSERVATIONS
 FROM ANY POPULATION WITH FINITE FIRST FOUR MOMENTS, COMPARED WITH THE CORRESPONDING
 MOMENTS OF THE STANDARD t DISTRIBUTION
 $\left(a \approx \frac{10}{a}\right)$

Function	Arbitrary, with finite first four moments	Normal
t	t_s	t_s
$\mu'_1(t)$	$-\frac{\gamma_{112}}{2\sqrt{N}} + o\left(\frac{1}{N^{3/2}}\right)$	0
$\mu'_2(t)$	$1 + \frac{2(1 + \gamma_{112})}{N} + o\left(\frac{1}{N^2}\right)$	$\frac{N-1}{N-2} = 1 + \frac{2}{N} + o\left(\frac{1}{N^2}\right)$
$\mu'_3(t)$	$-\frac{7\gamma_{112}}{2\sqrt{N}} + o\left(\frac{1}{N^{3/2}}\right)$	0
$\mu'_4(t)$	$3 \left\{ 1 + \frac{6}{N} \left[1 + \frac{14\gamma_{112}^2}{9} - \frac{\gamma_{112} - \frac{a^4}{120}}{9 \left(1 + \frac{1}{N^2}\right)} \right] + o\left(\frac{1}{N^2}\right) \right\}$	$\frac{3(N-1)^2}{(N-3)(N-5)} = 3 \left(1 + \frac{6}{N} \right) + o\left(\frac{1}{N^2}\right)$

It should be noted that $s_{x_R}^2$, and *not* its adjusted value given in Paragraph (2) of Sec. 4.4, is to be used in the denominator of t_{x_R} . If the adjusted value is used, giving

$$t'_{x_R} = \frac{\sqrt{N} (\bar{x}_R - \mu'_{t;x})}{\sqrt{s_{x_R}^2 - \frac{w^2}{12}}} \quad (17)$$

then, since $|t'_{x_R}| > |t_{x_R}|$, it is clear that significant values of t'_{x_R} will arise too frequently. Furthermore, when $s_{x_R}^2$ is less than $w^2/12$, the value of t'_{x_R} will be imaginary, and in such cases some convention regarding the value of t'_{x_R} to be recorded will be needed. In other words, as Fisher has stated, "These [Sheppard's] adjustments should be used for purposes of estimation, but not usually for tests of significance."*

The foregoing discussion carries over to the case where $s_{x_R}^2$ has been obtained by an analysis of variance, or otherwise, from values of x rounded to within $\pm w/2$ and has n degrees of freedom, provided the situation is such that \bar{x} and s_x^2 may be regarded as independently distributed. The only change required is to replace $N - 1$ by n throughout.

5. EFFECTS OF ROUNDING ON STATISTICAL ANALYSES OF SMALL NUMBERS OF OBSERVATIONS FROM A NORMAL POPULATION

5.1. Introduction

Although the results obtained above are independent of the value of N , the discussion up to this point has been concerned mainly with cases involving a large number of observations. An exception is the quotation from Student in Sec. 1, which discusses in detail the effects of a coarse rounding on samples of 4 from a nearly normal population. From this passage it is clear that in the case of small samples the discontinuities of the distributions of \bar{x}_R and $s_{x_R}^2$ are the most serious effect of the rounding. For a fixed N , the discontinuities of the distributions of \bar{x}_R and $s_{x_R}^2$ may be expected to increase in number (in any finite interval) but to decrease in seriousness as the width of the rounding interval w decreases, and, for a fixed w , to increase in number but decrease in seriousness as N increases; hence, it is clear that *largeness* of N has meaning only in conjunction with *smallness* of w .

5.2. Exact Distributions of $s_{x_R}^2$ in Samples of 2 and 3 from a Normal Population

5.2.1. Illustrative Distributions.—In order to throw light on the joint effect of w and N on the distribution of $s_{x_R}^2$ in small samples from a

FISHER, *Statistical Methods*, Sec. D of Appendix to Chap. III.

normal population, exact distributions of s_{xR}^2 in samples of 2 from a normal population have been computed for $w = \sigma, \sigma/2$, and $\sigma/4$. These are portrayed in Figs. 4.1, 4.2, and 4.3, where they are compared with

$$N=2, w=\sigma$$

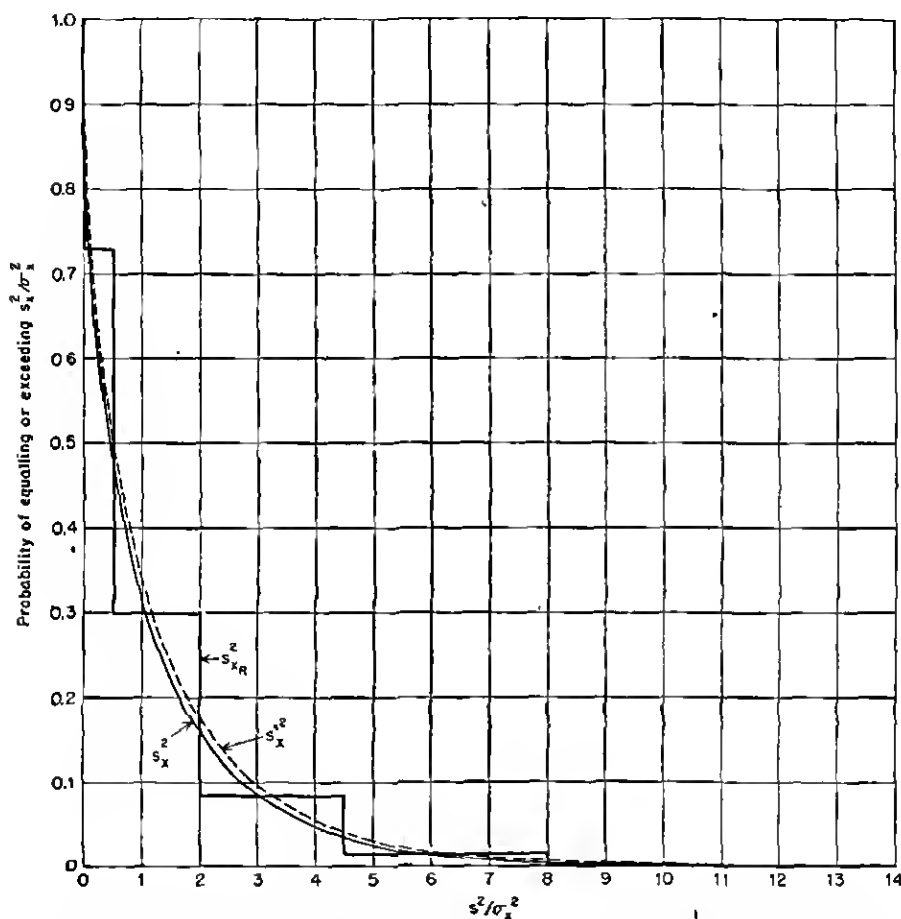


FIG. 4.1.—Distribution of s_{xR}^2 for samples of 2 from a normal population when the width of the rounding interval is one standard deviation, and corresponding continuous distributions of s_x^2 and $s_x'^2 = (13/12)s_x^2$.

the distribution of s_x^2 , which is distributed as $\chi^2\sigma^2$ for 1 degree of freedom. In Fig. 4.1 the distribution of

$$s_x'^2 = \left(1 + \frac{1}{12}\right) s_x^2 \quad (18)$$

is shown also, in view of (1) in Sec. 4.4.

The large steps in the distributions of $s_{x_R}^2$ shown in these figures emphasize the discontinuous character of these distributions. It follows from (1) of Sec. 4.4 that when N is large the distribution of $s_x'^2$ may be expected to graduate the distribution of $s_{x_R}^2$ more closely than will

$$N=2, w=\sigma/2.$$

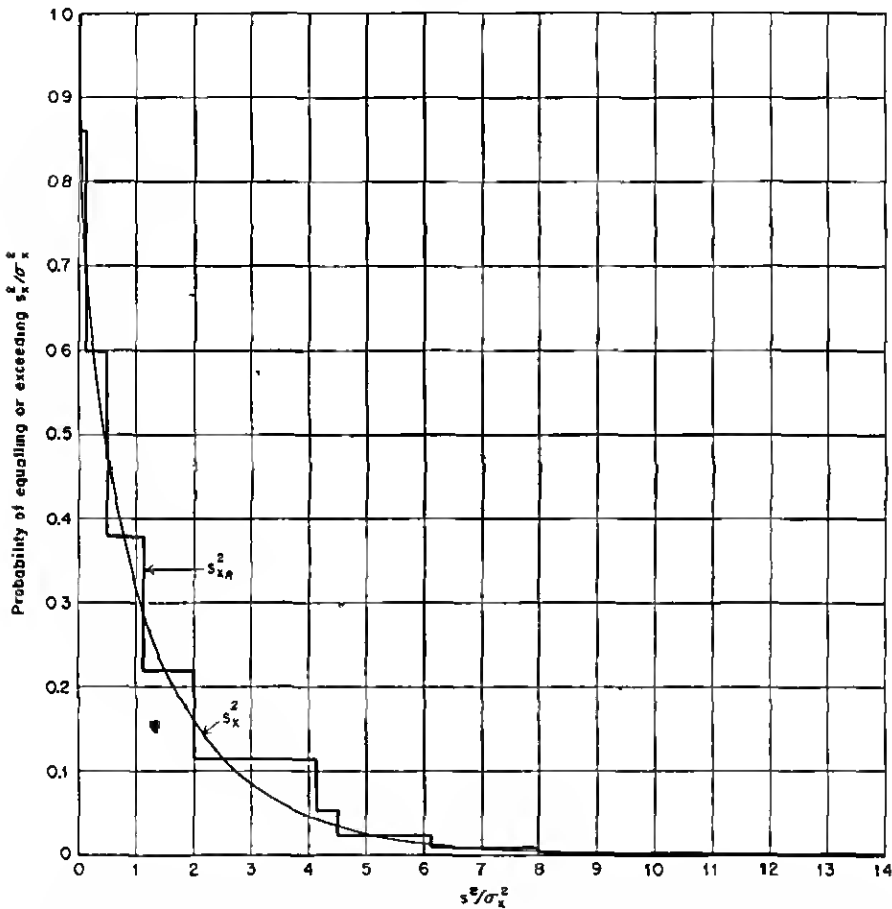


FIG. 4.2.—Distribution of $s_{x_R}^2$ for samples of 2 from a normal population when the width of the rounding interval is one-half standard deviation, and corresponding continuous distribution of s_x^2 .

the distribution of s_x^2 . From Fig. 4.1 it is clear that the improvement is negligible when $N = 2$ and $w = \sigma$. Furthermore, it is clearly impossible to find smooth curves that will approximate these step functions closely at all points. In other words, the probability of s_x^2 , or $s_x'^2$, equaling or exceeding a value u will approximate closely the probability of $s_{x_R}^2$ equaling or exceeding u only for certain values of u , principally those that

are near a point of intersection of the distribution curve of $s_{x_1}^2$ or $s_{x_2}^2$, with the horizontal portion of a step in the distribution of $s_{x_R}^2$.

Figure 4.4 compares the distribution of $s_{x_R}^2$ in samples of 3 from a normal population when $w = \sigma$ with the distribution of $s_{x_1}^2$, which is now

$$N=2, w=\sigma/4$$

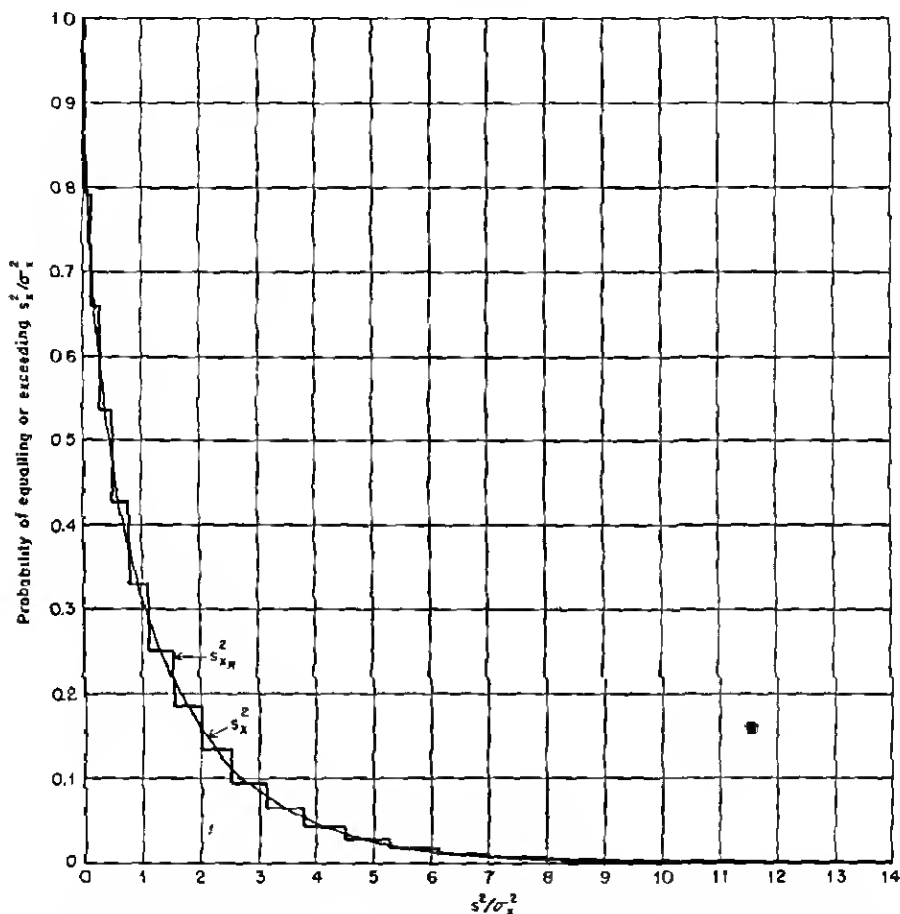


FIG. 4.3.—Distribution of $s_{x_R}^2$ for samples of 2 from a normal population when the width of the rounding interval is one-quarter standard deviation, and corresponding continuous distribution of $s_{x_1}^2$.

distributed as $\chi^2\sigma^2/2$ for 2 degrees of freedom. Comparison of Fig. 4.4 with Fig. 4.1 shows that increasing N from 2 to 3, with w fixed, has decreased the magnitudes of the steps, but not markedly.

5.2.2. Effect of the Position of the Rounding Lattice.—Before attempting to answer the question of how large N needs to be for a given value of w , and vice versa, in order that the approximation given in Paragraph

(1) of Sec. 4.4 can be used with confidence, it will be well to digress briefly on the effect of the position of the rounding lattice on the distribution of s_{xR}^2 when N and w are fixed.

$$N=3, w=\sigma$$

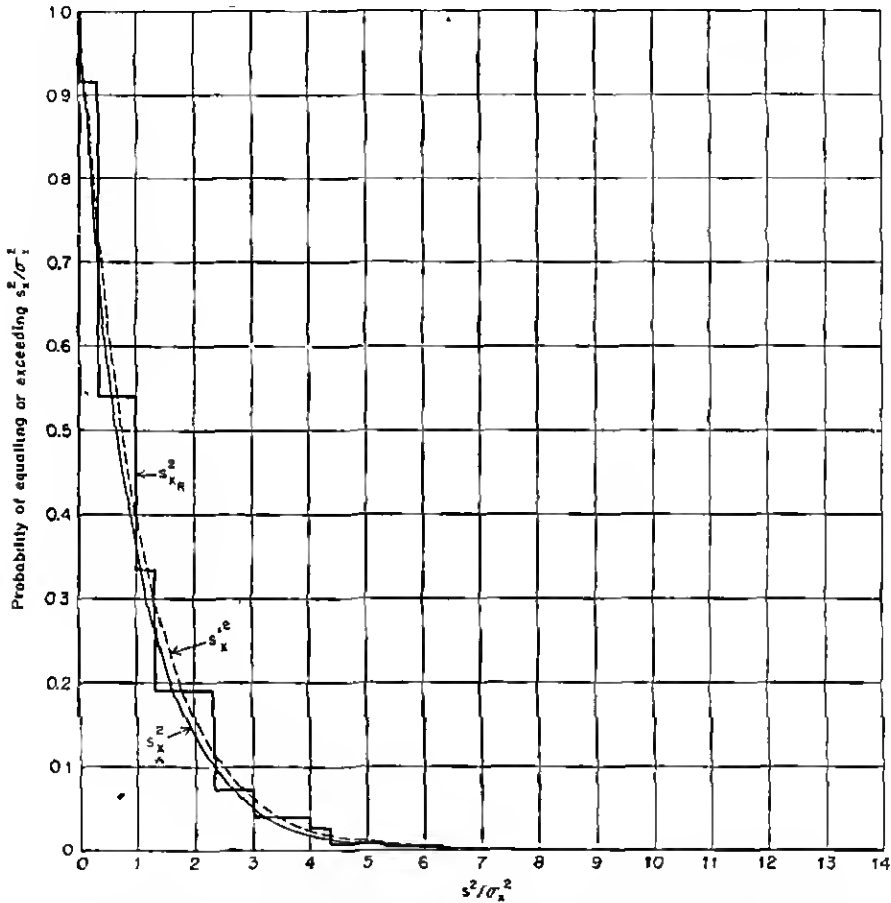


FIG. 4.4.—Distribution of s_{xR}^2 for samples of 3 from a normal population when the width of the rounding interval is one standard deviation, and corresponding continuous distribution of s_x^2 .

Tables 4.4 to 4.6 give to 7 decimal places the exact distributions of s_{xR}^2 for $N = 2$ and $w = \sigma, \sigma/2$, and $\sigma/4$, respectively, corresponding to two positions of the rounding lattice that are a half period* apart, when the

*Let ξ_i denote the value of x at the mid-point of the i th interval,

$$\xi_i - w/2 < x \leq \xi_i + w/2 \quad (i = 0, \pm 1, \pm 2, \dots, \pm \infty)$$

corresponding to a given location of the rounding lattice. Writing

sampling is from a normal population. These two positions have been chosen as follows:

Position I: The mean of x in the population coincides with the boundary between two of the rounding intervals. In the notation of the footnote, this means that if the mean of x in the population is chosen as the origin, so that $\mu'_{1,x} = 0$, then $\theta = -(2i - 1)\pi$, where i is some positive or negative integer, or zero.

TABLE 4.4
EXACT DISTRIBUTIONS OF $s_{2R}^2 = (x_{R1} - x_{R2})^2/2$ FOR THE EXTREME POSITIONS OF THE
ROUNDING LATTICE WHEN THE WIDTH OF THE ROUNDING INTERVAL IS ONE
STANDARD DEVIATION AND x_1 AND x_2 ARE INDEPENDENT OBSERVATIONS
FROM A NORMAL POPULATION
($N = 2$, $w = \sigma_x$)

u^*	Probability that $\frac{s^2}{\sigma_x^2} \geq u$	
	Position I	Position II
0	1.0000 000	1.0000 000
$1\frac{1}{2}$	0.7291 077	0.7200 858
2	0.2987 666	0.2987 802
$2\frac{1}{2}$	0.0832 659	0.0832 609
3	0.0152 891	0.0152 903
$3\frac{1}{2}$	0.0018 126	0.0018 124
4	0.0001 368	0.0001 368
$4\frac{1}{2}$	0.0000 065	0.0000 065
5	0.0000 002	0.0000 002
Over 5	0.0000 000	0.0000 000
$\frac{E(s_{2R}^2)}{\sigma_x^2}$	1.0833 332	1.0833 334
$\frac{V(s_{2R}^2)}{\sigma_x^4}$	2.3430 509	2.3430 491

* The values of u shown include every possible value up to 32.

Position II: The mean of x in the population coincides with the mid-point of a rounding interval. Thus $\theta = -2\pi i$, where i is some positive or negative integer, or zero.

$$\xi_i = \left(i + \frac{\theta}{2\pi}\right)w$$

θ may be used to define the location of the rounding lattice. Thus $\theta = 0$ when the mid-point of the 0th interval is at the origin ($x = 0$), and $\theta = \pi$ when the lower boundary of the 0th interval is at the origin. Clearly, the rounding is the same for $\theta = \varphi$ and $\theta = \varphi \pm 2k\pi$, where k is an integer.

Table 4.7 gives to 6 decimal places the exact distributions of $s_{x_R}^2$ for $N = 3$ and $w = \sigma$, corresponding to these two positions of the rounding lattice, when the sampling is from a normal distribution.

TABLE 4.5
EXACT DISTRIBUTIONS OF $s_{x_R}^2 = (x_{R1} - x_{R2})^2/2$ FOR THE EXTREME POSITIONS OF THE
ROUNDING LATTICE WHEN THE WIDTH OF THE ROUNDING INTERVAL IS
ONE-HALF STANDARD DEVIATION AND x_1 AND x_2 ARE INDEPENDENT
OBSERVATIONS FROM A NORMAL POPULATION

$$(N = 2, w = \frac{\sigma}{2})$$

u^*	Probability that $\frac{s^2}{\sigma^2} \geq u$		u^*	Probability that $\frac{s^2}{\sigma^2} \geq u$	
	Position I	Position II		Position I	Position II
0	1.0000 000	1.0000 000	$16\frac{3}{8}$	0.0000 110	0.0000 110
$\frac{1}{8}$	0.8604 037	0.8604 037	$49\frac{1}{2}$	0.0000 021	0.0000 021
$\frac{1}{4}$	0.5977 898	0.5977 898	$225\frac{1}{8}$	0.0000 004	0.0000 004
$\frac{3}{8}$	0.3792 359	0.3792 360	32	0.0000 001	0.0000 001
2	0.2183 109	0.2183 110	Over 32	0.0000 000	0.0000 000
$25\frac{1}{8}$	0.1134 753	0.1134 754	$\frac{E(s_{x_R}^2)}{\sigma_x^2}$	1.0208 312	1.0208 314
$\frac{5}{2}$	0.0530 515	0.0530 515	$\frac{V(s_{x_R}^2)}{\sigma_x^4}$		
$49\frac{1}{8}$	0.0222 398	0.0222 398			
8	0.0083 396	0.0083 396			
$31\frac{1}{8}$	0.0027 919	0.0027 919		2.0839 751	2.0839 755
$25\frac{1}{2}$	0.0008 331	0.0008 331			
$121\frac{1}{8}$	0.0002 213	0.0002 213			
18	0.0000 523	0.0000 523			

* The values of u shown include every possible value up to 32.

The probabilities given in these tables were evaluated with the aid of a 15-place table of the probabilities for normal deviates,* and are believed to be correct to within 1 unit in the last place shown. The calculations were carried to 10 decimals or more at all stages and were carefully checked. The individual probabilities obtained, when rounded to the number of places shown, sum to unity within ± 1 in the last place shown.

From these tables, and the fact that Positions I and II represent opposite extremes in their effects on $s_{x_R}^2$, the following conclusions may be drawn:

- (1) When $N = 2$, the probability that $s_{x_R}^2/\sigma^2$ equals or exceeds u is unaffected to 4 decimal places by the position of the rounding lattice if $w = \sigma$; to 7 decimal places, in general, if $w \leq \sigma/2$.
- (2) When $N = 3$, the probability that $s_{x_R}^2/\sigma^2$ equals or exceeds u

* Mathematical Tables Project, *Tables of Probability Functions*.

is unaffected by the position of the rounding lattice to 3 decimals if $w = \sigma$.

(3) The effect of the position of the rounding lattice on the distribution of $s_{x_R}^2$ appears to increase with the number of observations involved, that is, with N .

TABLE 4.6
EXACT DISTRIBUTIONS OF $s_{x_R}^2 = (x_{R1} - x_{R2})^2/2$ FOR THE EXTREME POSITIONS OF THE
ROUNDING LATTICE WHEN THE WIDTH OF THE ROUNDING INTERVAL IS
ONE-QUARTER STANDARD DEVIATION AND x_1 AND x_2 ARE INDEPENDENT
OBSERVATIONS FROM A NORMAL POPULATION
($N = 2, w = \frac{\sigma}{4}$)

u^*	Probability that $\frac{s^2}{\sigma^2} \geq u$		u^*	Probability that $\frac{s^2}{\sigma^2} \geq u$	
	Position I	Position II		Position I	Position II
0	1.0000 000	1.0000 000	$8\frac{1}{8}$	0.0020 043	0.0020 043
$\frac{1}{32}$	0.9296 594	0.9296 595	$36\frac{1}{32}$	0.0010 902	0.0010 902
$\frac{1}{8}$	0.7911 480	0.7911 481	$25\frac{1}{2}$	0.0005 759	0.0005 759
$\frac{3}{32}$	0.6589 474	0.6589 474	$44\frac{1}{32}$	0.0002 954	0.0002 954
$\frac{1}{2}$	0.5366 322	0.5366 322	$12\frac{1}{8}$	0.0001 471	0.0001 471
$2\frac{1}{32}$	0.4269 273	0.4269 273	$59\frac{1}{32}$	0.0000 711	0.0000 711
$\frac{3}{8}$	0.3315 445	0.3315 445	18	0.0000 333	0.0000 333
$4\frac{1}{32}$	0.2511 525	0.2511 525	$62\frac{1}{32}$	0.0000 151	0.0000 151
2	0.1854 693	0.1854 693	$16\frac{3}{8}$	0.0000 066	0.0000 066
$8\frac{1}{32}$	0.1334 464	0.1334 464	$72\frac{1}{32}$	0.0000 028	0.0000 028
$2\frac{1}{8}$	0.0935 041	0.0935 041	$4\frac{1}{2}$	0.0000 011	0.0000 011
$12\frac{1}{32}$	0.0637 758	0.0637 758	$84\frac{1}{32}$	0.0000 004	0.0000 004
$\frac{9}{2}$	0.0423 269	0.0423 269	$22\frac{1}{8}$	0.0000 001	0.0000 001
$16\frac{1}{32}$	0.0273 253	0.0273 253	Over $22\frac{1}{8}$	0.0000 000	0.0000 000
$4\frac{1}{8}$	0.0171 541	0.0171 541	$\frac{E(s_{x_R}^2)}{\sigma^2}$	1.9052 058	1.9052 058
$22\frac{1}{32}$	0.0104 691	0.0104 691			
8	0.0062 099	0.0062 099	$\frac{V(s_{x_R}^2)}{\sigma^4}$	2.0207 869	2.0207 869
$28\frac{1}{32}$	0.0035 793	0.0035 793			

* The values of u shown include every possible value up to $225/8$.

The mean and variance of $s_{x_R}^2/\sigma^2$ for each of the situations considered in Tables 4.4 to 4.7 are given in these tables. These values are brought together in Table 4.8, where they are compared with the corresponding *average* values computed from the formulas of Table 4.2. When $s_{x_R}^2$ is based on N independent (rounded) observations from a normal distribution, then the formula of Table 4.2 for the average variance of $s_{x_R}^2$

becomes

$$\text{average variance of } s_{x_R}^2 = \frac{2\sigma_x^4}{N-1} \left(1 + \frac{a^2}{12}\right) \left(1 - \frac{(N-1)a^4}{240N}\right) \quad (19)$$

where $a = w/\sigma^*$. Equation (19) gives the average value of the variance of $s_{x_R}^2$ in a series of repeated trials in each of which N independent

TABLE 4.7

EXACT DISTRIBUTIONS OF $s_{x_R}^2 = \sum_{i=1}^3 (x_{Ri} - \bar{x}_R)^2/2$ FOR THE EXTREME POSITIONS OF THE ROUNDING LATTICE WHEN THE WIDTH OF THE ROUNDING INTERVAL IS ONE STANDARD DEVIATION AND x_1 , x_2 , AND x_3 ARE INDEPENDENT OBSERVATIONS FROM A NORMAL POPULATION
($N = 3$, $w = \sigma_x$)

u^*	Probability that $\frac{s^2}{\sigma^2} \geq u$		u^*	Probability that $\frac{s^2}{\sigma^2} \geq u$	
	Position I	Position II		Position I	Position II
0	1.000 000	1.000 000	9	0.000 401	0.000 401
$\frac{1}{3}$	0.915 415	0.915 156	$2\frac{2}{3}$	0.000 278	0.000 278
1	0.541 194	0.541 514	$3\frac{1}{3}$	0.000 098	0.000 098
$\frac{4}{3}$	0.330 213	0.338 898	12	0.000 027	0.000 027
$\frac{5}{3}$	0.190 327	0.190 245	$3\frac{2}{3}$	0.000 019	0.000 019
3	0.071 985	0.072 096	13	0.000 008	0.000 008
4	0.040 097	0.040 103	$4\frac{2}{3}$	0.000 002	0.000 002
$1\frac{2}{3}$	0.027 447	0.027 411	16	0.000 001	0.000 001
$1\frac{5}{3}$	0.008 814	0.008 808	Over 16	0.000 000	0.000 000
$1\frac{7}{3}$	0.005 122	0.005 122	$\frac{E(s_{x_R}^2)}{\sigma_x^2}$	1.083 330	1.083 336
7	0.002 200	0.002 206			
$2\frac{2}{3}$	0.000 629	0.000 629	$\frac{V(s_{x_R}^2)}{\sigma_x^4}$	1.170 804	1.170 831

* The values of u shown include every possible value up to 16.

observations are drawn at random from a normal distribution, the position of the rounding lattice being determined at random independently for each trial. Since the average value of the mean of $s_{x_R}^2$ is unaffected by the nature of the distribution of x , its value is given by the formula of Table 4.2 in any case. From Table 4.8 it is seen that

* When N is large so that $(N-1)/N \doteq 1$, formula (19) agrees through the term in a^4 with the expression given by R. A. Fisher, "Mathematical Foundations," p. 362,

for the variance of $\sum_{i=1}^N (x_{Ri} - \mu'_{1|x})^2/N$ computed from N independent rounded observations from a normal population.

(1) When N is 2 or 3 and $w \leq \sigma$, the mean values of $s_{\bar{x}_R}^2$ for Position I and Position II of the lattice agree with each other and with their theoretical average values, to 5 decimal places or more.

(2) When N is 2 or 3 and $w = \sigma$, the variances of $s_{\bar{x}_R}^2$ for Position I and Position II of the lattice agree with each other and with their theoretical average values to 2 decimal places or more; when $w \leq \sigma/2$, to 3 decimal places or more.

TABLE 4.8

COMPARISON OF ACTUAL VALUES OF THE MEAN AND VARIANCE OF $s_{\bar{x}_R}^2/\sigma_x^2$ WITH THE VALUES IMPLIED BY THE FORMULAS OF TABLE 4.2 WHEN THE WIDTH OF THE ROUNDING INTERVAL IS ONE STANDARD DEVIATION (AND LESS) AND $s_{\bar{x}_R}^2$ IS BASED ON TWO OR THREE INDEPENDENT OBSERVATIONS FROM A NORMAL DISTRIBUTION

Number of observations, N	Width of rounding interval, σ units	Lattice position*	Mean value of $s_{\bar{x}_R}^2/\sigma_x^2$		Variance of $s_{\bar{x}_R}^2/\sigma_x^2$	
			Actual	By formula	Actual	By formula
2	1	I	1.0833 322	1.0833 333	2.3430 509	2.3423 322
	1	II	1.0833 334	1.0833 333	2.3430 491	2.3423 322
	$\frac{1}{2}$	I	1.0208 312	1.0208 333	2.0839 751	2.0839 300
	$\frac{1}{2}$	II	1.0208 314	1.0208 333	2.0839 755	2.0839 300
	$\frac{1}{4}$	I	1.0052 058	1.0052 083	2.0207 869	2.0208 711
	$\frac{1}{4}$	II	1.0052 058	1.0052 083	2.0207 869	2.0208 711
3	1	I	1.083 330	1.083 333	1.170 804	1.170 351
	1	II	1.083 336	1.083 333	1.170 831	1.170 351

* For the exact meanings of Position I and Position II, see Section 5.2.2.

Fisher* has studied the effect of the position of the rounding interval on the mean values of \bar{x}_R and $s_{\bar{x}_R}^2$ in samples from a normal distribution using an analytical approach based on the periodic character of such effects noted in the first footnote of this section. He has calculated that the bias of \bar{x}_R due to the position of a rounding lattice with intervals one standard deviation wide will be less than one-tenth the standard error of \bar{x}_R for values of N less than 1.379×10^{16} . For $s_{\bar{x}_R}^2$ the corresponding value of N is 1.75×10^{14} ; for the variance of $s_{\bar{x}_R}^2$, it is 1.34×10^{12} .

From (1) and (2) above and from Fisher's analysis, we conclude that

(3) The effect of the position of the rounding lattice on the mean and variance of \bar{x}_R and $s_{\bar{x}_R}^2$ in samples from a normal distribution is minute in comparison to the average effects of the rounding.

(4) In small samples (from a normal distribution at least), so far as the approximation of the distributions of \bar{x}_R and $s_{\bar{x}_R}^2$ by continuous distributions is concerned, the discontinuities of the distributions of \bar{x}_R

* FISHER, "Mathematical Foundations," pp. 318-321.

and $s_{z_n}^2$, caused by the rounding, are far more serious than the effects of the position of the rounding lattice.

5.3. Combinations of Sample Sizes and Rounding-interval Widths for Which the Actual Distribution of $s_{z_n}^2$ Can Be Approximated Satisfactorily by a Continuous Distribution, When the Sampling Is From a Normal Population

We have not found a rigorous answer to the question of how large the sample size N needs to be for a given rounding-interval width w and how small w needs to be for a given value of N before the χ^2 approximation given in Paragraph (1) of Sec. 4.4 will adequately represent the distribution of $s_{z_n}^2$ for most practical purposes. Since the discontinuities of the distribution of $s_{z_n}^2$ are the principal source of the difficulties encountered in attempting to represent the actual distribution of $s_{z_n}^2$ by a continuous distribution when N is small and w is comparatively large, it is clear that an answer depends on finding the combinations of N and w for which the discontinuities of the distribution of $s_{z_n}^2$ over any given interval are sufficiently numerous and the steps sufficiently small to render them negligible.

TABLE 4.9
PROBABILITY THAT A ZERO VALUE OF $s_{z_n}^2$ WILL BE OBTAINED WHEN $s_{z_n}^2$ IS BASED ON N INDEPENDENT ROUNDED OBSERVATIONS FROM A NORMAL DISTRIBUTION

Number of observations, N	Width of rounding interval in σ units ($a = w/\sigma$)			
	1	$\frac{1}{2}$	$\frac{1}{4}$	$\frac{1}{8}$
2	0.271	0.1396	0.0703	0.0302
3	0.085	0.0225	0.0057	0.0014
4	0.028	0.0038	0.0005-	0.0001-
5	0.009	0.0007		
6	0.003	0.0001+		
7	0.001+			

The combinations of N and w for which the discontinuities of the distribution of $s_{z_n}^2$ are negligible when the sampling is from a normal population could be determined by preparing, for wide ranges of values of N and w , tables of the actual distribution of $s_{z_n}^2$ analogous to Tables 4.4 to 4.7. The arithmetical labor of the calculations involved in the preparation of such tables is so enormous, however, that it seems advisable to devise some rule of thumb, which is intuitively sound, as a substitute for rigorous answers until the latter become available. Accordingly, we propose that the probability of $s_{z_n}^2$ equaling zero for given values of N and w , when the sampling is from a normal population, be used as a basis for deciding whether a given pair of values of N and w is satisfactory. To

be more explicit, we propose that $P\{s_{\bar{x}}^2 = 0|N, w\} \leq 0.001$, evaluated on the assumption that the sampling is from a normal population, be adopted as a tentative definition of the combinations of values of N and w for which the χ^2 approximation given in (1) of Sec. 4.4 provides a satisfactory approximation to the distribution of $s_{\bar{x}}^2$ for practical purposes.

Values of $P\{s_{\bar{x}}^2 = 0|N, w\}$, for sampling from a normal population, are given in Table 4.9 for various combinations of values of N and w , the latter being expressed in units of the population standard deviation. It appears from this table that satisfactory combinations, where $a = w/\sigma$, are

$$\begin{array}{ll} a \leq 1/200, & N \geq 2 \quad (\text{by extrapolation}) \\ a \leq 1/10, & N \geq 3 \\ a \leq 1/3, & N \geq 4 \\ a \leq 1/2, & N \geq 5 \\ a \leq 2/5, & N \geq 6 \\ a \leq 1, & N \geq 7 \end{array} \quad (20)$$

The fact that the combinations (20) represent a somewhat arbitrary definition of the circumstances under which (1) and (3) of Sec. 4.4 may be expected to yield satisfactory results in practical work should not be lost sight of. Nor should the combinations (20) be regarded as competing with, or contradicting, the general recommendation, cited in the first paragraph of Sec. 4.1, that w be taken less than $\sigma/3$, or better, less than $\sigma/4$. The object of this general recommendation is to limit the inevitable loss of precision of estimates of parameters caused by rounding, and relates to the case where the choice of a rounding interval is yet to be made. Combinations (20), on the other hand, are not concerned with the loss of precision of estimates as a consequence of coarse rounding but are proposed as a rough indication of the circumstances under which data can be validly analyzed by simple modifications of standard procedures.

5.4. Distribution of Student's t and the Variance Ratio When Based on a Small Number of Rounded Observations

Like the distributions of all functions of rounded observations, the distribution of $t_{\bar{x}}$, defined in equation (16) of Sec. 4.5, is discontinuous. However, since the discontinuities of the distribution of \bar{x}_R and the distribution of $s_{\bar{x}}$ jointly affect the distribution of $t_{\bar{x}}$, its discontinuities are more numerous in any given interval than those of the distributions of \bar{x}_R and $s_{\bar{x}}$, and, generally, the steps are smaller than those of the distribution of $s_{\bar{x}}$. On the other hand, whenever $s_{\bar{x}}$ equals zero, this causes $t_{\bar{x}}$ to be either $+\infty$ or $-\infty$, according to the sign of the numerator with the exception of those cases in which \bar{x}_R equals the population mean

$\mu'_{1:z}$, when t_{z_R} can be defined to be equal to $+1$ or -1 , the sign being determined in a given instance by a random mechanism giving each sign equal probability.* The last-mentioned situation cannot occur unless $\mu'_{1:z}$ is a multiple of $1/N$ and will occur very rarely even when it is a possibility. On the other hand, it can be seen from Table 4.9 that infinite values of t_{z_R} may occur with annoying frequency in very small samples, for example $N \leq 4$, when coarse rounding is involved. If, however, the rounding employed with a given N is in accord with the recommendations (20), then the probability of an infinite value of t_{z_R} will be less than 0.001. Furthermore, the rounding so chosen will simultaneously render the steps in the distribution of t_{z_R} negligible, so that for practical purposes t_{z_R} may be regarded as following the standard t distribution, which is strictly valid only for t_z .

Similar considerations apply to the distribution of the ratio F_R of two mean squares, $s^2_{1z_R}$ and $s^2_{2z_R}$, which are such that in the absence of the rounding $n_1 s^2_1$ and $n_2 s^2_2$ would be distributed independently as $\chi^2 \sigma^2$ for n_1 and n_2 degrees of freedom, respectively. In particular, $F_R = s^2_{1z_R}/s^2_{2z_R}$ will equal 0 whenever $s^2_{1z_R}$ is 0; it will equal infinity whenever $s^2_{2z_R}$ is 0; it may be defined to be 1 when both $s^2_{1z_R}$ and $s^2_{2z_R}$ are 0. Four exact distributions of F_R were calculated from the distributions of $s^2_{z_R}$ given in Tables 4.4 to 4.7. The cases considered were $n_1 = n_2 = 1$, $w = \sigma, \sigma/2, \sigma/4$; $n_1 = n_2 = 2$, $w = \sigma$. As expected, the discontinuities of F_R were more numerous in any given interval than the discontinuities of the distribution of $s^2_{z_R}$ alone, and the steps were smaller. The biggest steps were those corresponding to $F_R = 0$, $F_R = 1$, and $F_R = +\infty$. From the graphs that were sketched it was apparent that if these three steps were reduced to negligible size, either by increasing n_1 and n_2 or by decreasing w , then the distribution of F_R would be represented by the F distribution to an approximation sufficient for most practical purposes. It is believed that if the $N_1 (= n_1 + 1)$, $N_2 (= n_2 + 1)$, and the common rounding interval satisfy the recommendations (20) above, then F_R may be regarded as distributed according to the F distribution for most practical purposes.

If $s^2_{1z_R}$ and $s^2_{2z_R}$ correspond to different roundings w_1 and w_2 , then the distribution of F_R will be biased relative to the distribution of F . This bias cannot be eliminated when σ^2 is unknown, the situation in which F tests are customarily employed.

6. STATISTICAL PROPERTIES OF TABULAR AND INTERPOLATED VALUES

It is often stated, or implied, in statistical texts that the error of a tabular entry may be regarded as a random variable distributed with a

* The complication of this definition arises because $F = \mathcal{Y}_0^2 = 1$ seems a sensible definition, and $t = \mathcal{Y}_0 = 0$ also seems sensible, but $t^2 = F$. The complication avoids the implication that $0^2 = 1$.

uniform probability density between minus $\frac{1}{2}$ unit and plus $\frac{1}{2}$ unit in the last place. Clearly the rounding error of a given tabular entry has a definite value, although it may be unknown to a user of the table. Hence the error of a given tabular entry is not a random variable in any meaningful sense of the expression, its distribution being concentrated at a point. Therefore, the statement appearing in statistical texts must be intended to mean that when one is carrying out computations involving the use of a large number of different tabular numbers, the errors of the individual tabular numbers considered collectively will, under favorable circumstances, range from minus $\frac{1}{2}$ unit to plus $\frac{1}{2}$ unit in the last place with approximately uniform density.

The circumstances may sometimes be quite unfavorable. Thus in a given computation involving the use of numbers from only a small section of a table—and in certain other less easily specified cases also—the errors may all tend to have the same sign or to be bunched in some other manner characteristic of the values of the function when expressed to the given number of decimal places for that particular range of the argument. Indeed, the favorability of the circumstances may depend on the units in which the function is tabulated, as the following parallel portions of two logarithm tables illustrate:

N	$\log_{10} N$	$\log_e N$
9861	3.9939 210	9.1963 429
9862	3.9939 650	9.1964 443
9863	3.9940 090	9.1965 457
9864	3.9940 531	9.1966 470
9865	3.9940 971	9.1967 484
9866	3.9941 411	9.1968 498
9867	3.9941 851	9.1969 511
9868	3.9942 291	9.1970 525
9869	3.9942 731	9.1971 538
9870	3.9943 172	9.1972 551
9871	3.9943 612	9.1973 564
9872	3.9944 051	9.1974 577
9873	3.9944 491	9.1975 590
9874	3.9944 931	9.1976 603
9875	3.9945 371	9.1977 616
9876	3.9945 811	9.1978 629
9877	3.9946 251	9.1979 641
9878	3.9946 690	9.1980 653
9879	3.9947 130	9.1981 666

These logarithms are given above correct to 7 decimal places. From an examination of the digits in the seventh place in the case of the values of

$\log_{10} N$, it is apparent that if one is calculating with the aid of logarithms read from a 6-place table of $\log_{10} N$, and the values of N involved are limited to the range shown above, the errors of the logarithms will be bunched around a value of one-tenth unit in the sixth place and quite definitely will not be distributed more or less uniformly from minus $\frac{1}{2}$ unit to plus $\frac{1}{2}$ unit in the sixth place. On the other hand, if the computations are carried out with the aid of a 6-place table of $\log_e N$, then even though the values of N involved are confined to the range shown above, the errors of the logarithms may be fairly uniformly distributed between minus $\frac{1}{2}$ unit and plus $\frac{1}{2}$ unit in the sixth place, although there will be a gap in the distribution of the error in the vicinity of two-tenths unit in the last place.

Since there is a definite relationship between the exact values of a function for successive values of the argument, there is likewise a definite relationship between the errors due to rounding in the tabular values given correct to n decimal places. Hence the errors due to rounding to n places are never actually equivalent to independent observed values of a random variable uniformly distributed between minus $\frac{1}{2}$ and plus $\frac{1}{2}$ unit in the last place retained. Nevertheless, if a large number of entries, corresponding to widely dispersed values of the argument, are examined, the figures beyond the n th place will often form decimal fractions that appear to be more or less uniformly and independently distributed between 0 and 1 in units of the last figure retained; in some cases, this is true even for relatively small values of n . Furthermore, when the function tabulated is irrational or transcendental, the larger the value of n , the more nearly do the decimals beyond the n th place form decimal fractions that seem to be uniformly and independently distributed, for a given spacing of the argument. There are exceptions, of course. For example, the functions $10^m/9$, $10^m/99$, $10^m/999$, etc. for $m = 0, \pm 1, \pm 2, \dots$, which have only 0's and 1's in their decimal expansions, do not exhibit either of the aforementioned properties. Similarly, tables of good functions may have some bad patches. However, the fact that the above properties are quite common, especially in the case of decimal expansions of irrational and transcendental numbers, suggests that in many cases it may be useful to regard the errors in tabular numbers due to rounding as uniformly and independently distributed between plus $\frac{1}{2}$ and minus $\frac{1}{2}$ unit in the last place tabulated—provided one exercises reasonable judgment in applying the deductions from this assumption in individual cases.

Let us assume then, with the foregoing reservations, that when the error of a tabular number due to rounding lies between $\pm w/2$, the error ϵ is distributed with uniform probability density between $\pm w/2$. It follows immediately that

$$\text{Mean error} = \frac{1}{w} \int_{-\frac{w}{2}}^{+\frac{w}{2}} \epsilon \, d\epsilon = 0 \quad (21)$$

$$\sigma_{\epsilon}^2 = \text{variance of errors} = \frac{1}{w} \int_{-\frac{w}{2}}^{+\frac{w}{2}} \epsilon^2 \, d\epsilon = \frac{w^2}{12} = 0.0833w^2 \quad (22)$$

whence the standard deviation of the errors is

$$\sigma_{\epsilon} = \frac{w}{\sqrt{12}} = 0.2887w \quad (23)$$

Consequently, if rounding errors are viewed from this statistical viewpoint, equation (21) implies that rounding is unbiased, that is, the average difference between the rounded tabular entry and the true value of the function will be zero. Maintaining the statistical viewpoint, it follows that the sum of the errors of k entries that are "correct" to within $\pm w/2$, assuming independence of the errors, will be distributed about a mean of zero with a standard deviation of $w\sqrt{k/12}$; furthermore, the distribution is approximately normal (Gaussian) for $k > 4$.*

As an example of the use of this result, consider a tabulation, supposedly correct to 5 decimals, of the nine terms in the expansion of $(p+q)^8$ for $p = \pi/6$. The sum of the nine values is 1.00003. Does this discrepancy of 0.00003 from the true sum suggest that a mistake has been made in the calculations? The maximum admissible discrepancy is bounded by ± 0.000045 , so there is no positive proof that the calculations are in error. The observed discrepancy, measured in units of 0.00001, corresponds approximately to a normal deviate of

$$\frac{(3 - 0)}{\sqrt{9/12}} = 3.46.$$

Since the probability of a normal deviate differing from 0 by more than 2.576 is less than 0.01,† it is advisable to check the calculations (probably starting with the sum).

Fisher and Wishart‡ have used the statistical viewpoint to determine the distribution of the error of an interpolated value when the values of the argument are equally spaced. Let the spacing of the argument be taken as unity, and let 0 to 1 represent the interval containing the value

* For details, see the papers by Baten, Hall, Irwin, and Rietz listed in Sec. 7.

† This may be verified from Table 1.1 of Chap. 1, since the probability is 2(0.005) that a normal deviate will be either above $K_{0.005}$ or below $-K_{0.005}$.

‡ FISHER and WISHART, "On the Distribution of the Error of an Interpolated Value."

of the argument p for which it is desired to obtain an interpolated value; then, if the interpolation is performed without recourse to differences, using Lagrangian interpolation coefficients,* the error of the interpolate can be expressed simply in terms of the tabular entries used to obtain it. It is, in fact, the "interpolate" of the errors:

$$\text{Error of linear (2-point) interpolate} = (1 - p)\epsilon_0 + p\epsilon_1$$

$$\text{Error of quadratic (3-point) interpolate}$$

$$= \frac{p(p-1)\epsilon_{-1} + 2(1-p^2)\epsilon_0 + p(p+1)\epsilon_1}{2} \quad (24)$$

$$\text{Error of } (2m)\text{-point interpolate} = \sum_{k=-m+1}^m A_k^{2m}(p) \cdot \epsilon_k$$

$$\text{Error of } (2m+1)\text{-point interpolate} = \sum_{k=-m}^m A_k^{2m+1}(p) \cdot \epsilon_k$$

If the errors of the tabular entries may be regarded as independent random variables with a common variance σ^2 , then the variance of an r -point interpolate for argument p is simply

$$V(p, r) = \sum_k [A_k^r(p)]^2 \cdot \sigma^2 \quad (25)$$

where the summation is over k from $-m+1$ to m when $r = 2m$, and over k from $-m$ to $+m$ when $r = 2m+1$. In particular†

$$\begin{aligned} V(p, 2) &= \text{variance of 2-point Lagrangian interpolate} \\ &= [(1-p)^2 + p^2]\sigma^2 = [1 - 2p(1-p)]\sigma^2 \quad 0 \leq p \leq 1 \end{aligned} \quad (26)$$

and

$$\begin{aligned} V(p, 3) &= \text{variance of 3-point Lagrangian interpolate} \\ &= \frac{[p^2(p-1)^2 + 4(1-p^2)^2 + p^2(p+1)^2]\sigma^2}{4} \\ &= \frac{[6p^2(p^2-1) + 4]\sigma^2}{4} \quad 0 \leq p \leq 1. \end{aligned} \quad (27)$$

It can be determined readily by differentiation that the minimum value of $V(p, 3)$ corresponds to $p = \pm 1/\sqrt{2}$ and equals

$$\frac{5\sigma^2}{8} = 0.62500\sigma^2$$

* For numerical values of these coefficients for 3-point up to 11-point interpolation, see Mathematical Tables Project, *Tables of Lagrangian Interpolation Coefficients*; formulas for these coefficients are given in the introduction to the tables.

† Expression (26) is identical to that given by Fisher and Wishart, p. 914. In place of (27) they give an equivalent expression in terms of a variable p that varies from 0 to 1 when the p of (27) varies from $-1/2$ to $+1/2$.

which exceeds the minimum value of $V(p, 2)$, namely $\sigma^2/2 = 0.50000\sigma^2$, which corresponds to $p = \frac{1}{2}$. Also, for $0 \leq p \leq 1$, it is clear that the maxima are $V(0, 2) = V(0, 3) = V(1, 2) = V(1, 3) = \sigma^2$. Table 4.10 shows the minima and the average values of $V(p, r)$, $0 \leq p \leq 1$, in the case of $(2m)$ -point interpolation ($m = 1, 2, 3, 4$), and the practical minima* and the average values for $-\frac{1}{2} \leq p \leq \frac{1}{2}$ in the case of $(2m + 1)$ -point interpolation ($m = 0, 1, 2, 3$).

TABLE 4.10

MINIMUM AND AVERAGE VALUES OF THE VARIANCE OF AN r -POINT INTERPOLATE FOR AN ARGUMENT BETWEEN 0 AND 1 WHEN r IS EVEN, AND BETWEEN $-\frac{1}{2}$ AND $+\frac{1}{2}$ WHEN r IS ODD, THE VALUES OF THE ARGUMENT BEING SPACED AT UNIT INTERVALS AND THE ERRORS OF THE TABULAR ENTRIES BEING INDEPENDENTLY DISTRIBUTED WITH A COMMON VARIANCE σ^2

Interpolate	Minimum Variance* (units of σ^2)	Average Variance† (units of σ^2)
1-point (an entry)	1.00000	1.00000
2-point (linear)	0.50000	0.66666
3-point	0.71875	0.89375
4-point	0.64062	0.77566
5-point	0.74060	0.89574
6-point	0.70599	0.82244
7-point	0.76579	0.90291
8-point	0.74533	0.84942
...
infinite-point	1.00000	1.00000

* In the case of $(2m)$ -point interpolation, the values shown are actual minima, occurring at $p = \frac{1}{2}$; and in the case of $(2m + 1)$ -point interpolation, they are practical minima, occurring at $p = \pm \frac{1}{2}$. For explanation, see text.

† From Fisher and Wishart, pp. 914-915. The average has been taken over the interval $0 \leq p \leq 1$ in the case of $(2m)$ -point interpolates; over the interval $-\frac{1}{2} \leq p \leq +\frac{1}{2}$ in the case of $(2m + 1)$ -point interpolates.

In summary, if the errors of the tabular entries may be regarded as independent random variables with a common variance σ^2 , if the values of the argument are uniformly spaced at unit intervals, and if r -point interpolation for the interpolate corresponding to argument p , with $0 < p < 1$ for r even and $-\frac{1}{2} < p < +\frac{1}{2}$ for r odd, is carried on without differences, then

(1) The variance of the random error of the interpolate is always less than the variance of a single tabular entry.

* In the case of $(2m + 1)$ -point interpolation for $\frac{1}{2} < p < 1$, a more accurate interpolate can be obtained by taking $p = 1$ as origin, dropping the tabular entry for $k = -m$, adding the entry for $k = m + 1$, and using $1 - p$ as argument. With this convention, $V(p, 2m + 1)$ will have a practical minimum at $p = \pm \frac{1}{2}$, although actual minima occur at $p = \pm p'$ with $|p'| > \frac{1}{2}$.

(2) The variance of the random error of the interpolate is least for linear (2-point) interpolation.

(3) The variance of the random error of a $(2m + 2)$ -point interpolate is *greater* than the variance of the random error of a $(2m)$ -point interpolate, but *less* than the variance of the random error of a $(2m + 1)$ -point interpolate.

(4) The variance of the random error of a $(2m + 3)$ -point interpolate is greater than the variance of the random error of a $(2m + 1)$ -point interpolate.

From (3) and (4) it is clear that, if $(2m)$ -point interpolation does not yield the accuracy desired, but either $(2m + 1)$ -point or $(2m + 2)$ -point will,* then it may be advisable to employ $(2m + 2)$ -point rather than $(2m + 1)$ -point interpolation in order to minimize the loss of precision.

It should be noted that these results require merely that the errors of the successive tabular entries be regarded as independently distributed with a common variance—it is not assumed that the errors are due solely to rounding and are distributed with uniform probability density between $-w/2$ and $+w/2$. The results are, of course, applicable to this case, with $\sigma^2 = w^2/12$, as given by (22), when the independence assumption is tenable. Fisher and Wishart point out, however, that in this latter case the distribution of the error of the interpolate is more or less intractable, and does not tend to the normal (Gaussian) distribution (β_2 tends to 2.2 and not to 3) as r increases. This somewhat limits the usefulness of the standard deviation as a measure of the random error of the interpolate, although the inequalities of Tchebycheff and of Camp and Meidell are still applicable.† Since, by (24), the error of an interpolate is a linear function of the errors of the tabular entries when the interpolation is carried out without recourse to differences (that is, by using Lagrangian interpolation coefficients), the error of the interpolate will be normally distributed when the individual errors are independently and normally distributed with a common variance. Accordingly, they note that a table printed to one or two places more than are correct is capable of yielding a more accurate and more precise interpolate than the same table with the entries cut down, provided that the standard deviation of an entry is given and the errors are approximately normally and independently distributed about a mean of zero with a common variance.

* The reader is cautioned against inferring that $(r + 1)$ -point, $(r + 2)$ -point, and so forth, interpolation always yields greater accuracy than r -point interpolation; he is referred to Steffensen, *Interpolation*, pp. 34–53, for a discussion of the number of points to be used in a given instance and for a simple example in which the accuracy becomes worse as r increases.

† See, for instance, SHEWHART, *Economic Control of Quality*, pp. 176–177.

7. REFERENCES

- ABERNATHY, JOHN R.: "On the Elimination of Systematic Errors due to Grouping," *Annals of Mathematical Statistics*, Vol. 4 (1933), pp. 263-277.
- BATEN, W. D.: "Combining Constant Probability Functions," *American Mathematical Monthly*, Vol. 37 (1930), pp. 423-434.
- : "Corrections for the Moments of a Frequency Distribution in Two Variables," *Annals of Mathematical Statistics*, Vol. 2 (1931), pp. 309-319.
- CARVER, H. C.: "The Fundamental Nature and Proof of Sheppard's Corrections," *Annals of Mathematical Statistics*, Vol. 7 (1936), pp. 154-163.
- CAYLEY, ARTHUR: Letter to J. W. L. Glaisher (1874), reproduced (in part) in *Mathematical Tables and Other Aids to Computation*, Vol. 1 (1943-1945), p. 98.
- CRAIG, CECIL C.: "Sheppard's Corrections for a Discrete Variable," *Annals of Mathematical Statistics*, Vol. 7 (1936), pp. 55-61.
- ELBERTON, W. PALIN: "Adjustments for the Moments of J-Shaped Curves," *Biometrika*, Vol. 25 (1933), p. 179.
- FISHER, R. A.: "Applications of 'Student's' Distribution," *Metron*, Vol. 5 (1926) pp. 90-104.
- : "Frequency Distribution of the Values of the Correlation Coefficient in Samples from an Indefinitely Large Population," *Biometrika*, Vol. 10 (1915), pp. 507-521.
- : "On a Distribution Yielding the Error Function of Several Well-known Statistics," *Proceedings of the International Mathematical Congress*, Toronto (1924), Vol. 2, pp. 803-813.
- : "On the Mathematical Foundations of Theoretical Statistics," *Philosophical Transactions of the Royal Society of London*, Vol. 222A (1922), pp. 309-368.
- : *Statistical Methods for Research Workers*, 4th and later ed., Oliver and Boyd, Ltd., Edinburgh and London, 1933-1944.
- , and WISHART, J.: "On the Distribution of the Error of an Interpolated Value, and on the Construction of Tables," *Proceedings of the Cambridge Philosophical Society*, Vol. 23 (1927), pp. 917-921.
- GEARY, R. C.: "The Distribution of 'Student's' Ratio for Non-normal Samples," *Supplement to the Journal of the Royal Statistical Society*, Vol. 3 (1936), pp. 178-184.
- HALL, PHILIP: "The Distribution of Means of Samples of Size N drawn from a Population in Which the Variate Takes Values between 0 and 1, All Such Values Being Equally Probable," *Biometrika*, Vol. 29 (1927), pp. 240-244.
- IRWIN, J. O.: "On the Frequency Distribution of Means of Samples from a Population Having Any Law of Frequency with Finite Moments, with Special Reference to Pearson's Type II," *Biometrika*, Vol. 29 (1927), pp. 226-239.
- KENDALL, M. G.: "The Conditions under which Sheppard's Corrections Are Valid," *Journal of the Royal Statistical Society*, Vol. 101 (1938), pp. 592-605.
- LANGDON, W. H., and ORE, OYSTEIN: "Semi-Invariants and Sheppard's Corrections," *Annals of Mathematics*, Vol. 31 (1930), pp. 230-232.
- Mathematical Tables Project, Work Projects Administration, Federal Works Agency: *Tables of Lagrangian Interpolation Coefficients*, New York, Columbia University Press, 1944, 392 + xxxvi pp.
- : *Tables of Probability Functions, Volume II*, National Bureau of Standards, Washington, D.C., 1942, 344 + xxi pp.
- PAIRMAN, ELEANOR, and PEARSON, KARL: "On Corrections for the Moment Coefficients of Limited Range Frequency Distributions When There Are Finite or

- Infinite Ordinates and Any Slopes at the Terminals of the Range," *Biometrika*, Vol. 12 (1918-1919), p. 231.
- PEARSE, G. E.: "On Corrections for Moment Coefficients of Frequency Distributions When There Are Infinite Ordinates at One or Both Terminals of the Range," *Biometrika*, Vol. 20A (1928), p. 314.
- PEARSON, KARL: "Note on Mr. Palin Elderton's Corrections to Moments of J-curves," *Biometrika*, Vol. 25 (1933), p. 180.
- RIETZ, H. L. (editor): *Handbook of Mathematical Statistics*, Houghton Mifflin Company, Boston, 1924, 221 + viii pp.
- : "On a Certain Law of Probability of Laplace," *Proceedings of the International Mathematical Congress*, Toronto (1924), Vol. 2, pp. 795-799.
- SHEPARD, W. F.: "On the Calculation of the Most Probable Values of Frequency Constants, for Data Arranged According to Equidistant Divisions of a Scale," *Proceedings of the London Mathematical Society*, Vol. 29 (1898), pp. 353-380.
- SHEWHART, W. A.: *Economic Control of Quality of Manufactured Product*, D. Van Nostrand Company, Inc., New York, 1931, 501 + xiv pp.
- STEFFENSEN, J. F.: *Interpolation*, The Williams & Wilkins Company, Baltimore, 1927, 248 + ix pp.
- STUDENT, "The Probable Error of a Mean," *Biometrika*, Vol. 6 (1908), pp. 1-25; reprinted in *Student's Collected Papers*, ed. by E. S. Pearson and J. Wishart, *Biometrika* Office, University College, London, 1942, 224 + xiv pp.
- WOLD, HERMAN: "Sheppard's Correction Formulae in Several Variables," *Skandinavisk Aktuarietidskrift*, Vol. 17 (1934), pp. 248-255.

CHAPTER 5

ACCEPTANCE INSPECTION WHEN LOT QUALITY IS MEASURED BY THE RANGE

	PAGE
1. Type of Problem.	227
2. Method of Solution	228
3. Single Sampling	231
4. Sequential Sampling	232
5. References.	234

FIGURES

5.1 Cumulative Probability Distribution of the Range in Samples of k from a Normal Population	230
5.2 OC and ASN Curves for Sequential Sampling Plan Based on Standard Deviation: $\sigma_1 = 0.05556$, $\sigma_2 = 0.07143$, $\alpha = 0.01$, $\beta = 0.01$; $h_1 = 0.07180$, $h_2 = 0.07180$, $s = 0.003927$	234

This chapter was prepared by the editors.

With the exception of Sec. 3, it is based on a memorandum by
M. A. Girshick, U.S. Bureau of the Census

CHAPTER 5

ACCEPTANCE INSPECTION WHEN LOT QUALITY IS MEASURED BY THE RANGE

1. TYPE OF PROBLEM

The range, defined as the difference between the largest and smallest observations in a sample, is familiar in industrial experimentation and quality control as a measure of dispersion in samples. Many applications of the range are to normal or nearly normal populations, for which the variability is better characterized by the standard deviation. The range is used to measure dispersion in samples because of the ease with which it can be determined, and because in small samples it is almost as efficient a measure of variability as the standard deviation.* The present chapter is concerned with an interesting reversal of these roles, where the variability of the lot or process is characterized in terms of the range itself but where the standard deviation is used as the sampling statistic in acceptance inspection to determine whether the range meets specified requirements.

One type of problem in which the range is the parameter of primary interest is that of ensuring the virtual simultaneity of a set of events. This set of events may be thought of as a random sample of k units from an underlying population of such events, and the requirement of simultaneity as a demand that the time difference between the occurrence of the first and last event of such a sample be small. In practice, of course, some samples will meet this requirement and others will not, but we can formulate the requirement statistically as follows: Let the size of the

* One statistic is more efficient than another if it varies less from sample to sample for a fixed population, that is, if its sampling variability is less. To get a basis of comparison, it is necessary to convert values of one statistic into implied values of the other. For example, given the range of a sample of N from a normal population, an estimate of the standard deviation can be made with the aid of Tippett's table of the mean range, in units of the population standard deviation, for samples of N from a normal population. Such an estimate will vary more from sample to sample than if the standard deviation had been computed directly by the usual formula. Conversely, given the sample standard deviation, an estimate of the sample range can be formed; such an estimate will vary less from sample to sample than if the range had been computed directly. For samples of 2, however, the range and standard deviation are equally variable; for samples of 3 the range is slightly more variable than the standard deviation, and as the sample size increases the variability of the range increases relative to that of the standard deviation. (For full citations, see Sec. 5.)

Chap. 3, Sec. 4.4, pp. 160-163, discusses the efficiency of statistics.

sample be k , and let t_i ($i = 1, 2, \dots, k$) be the time of occurrence of the i th event of the sample measured from an arbitrary time origin. Denote by R_k the difference between the longest and the shortest of these times in a particular sample. Then the requirement for an acceptable lot is that in not more than a fraction γ of samples of k shall the range R_k exceed a fixed value U . If the time can be measured for each item in the lot, it may be possible to form sets of k in such a way that the range is satisfactory in all or nearly all sets. On the other hand, if determination of the time alters or destroys the unit, if the time varies from one trial to another for a given unit, or if measurement of the times and systematic grouping is expensive, there are advantages to a procedure such as that suggested, based on random grouping.

A typical problem of ensuring temporal simultaneity arises in connection with mechanisms for which there is a certain lapse of time between activation—for example, closing a switch—and operation. If such mechanisms are used in assemblies of two or more activated from a single source, it may be important to the functioning of the assembly that these time lapses be nearly equal, in other words, that all the operations occur within a brief interval. This need can be fulfilled by requiring that each lot of the component mechanisms be such that the range of delay times in random sets of k mechanisms be less than some predetermined constant. It is not possible, without testing the entire lot, to assure that every set of k formed at random from a lot will have an acceptable range; but it is possible by sampling inspection to obtain any required level of assurance, short of certainty, of detecting lots worse than any specified quality P , as measured by the percentage of sets of k in which the range is too large.

Problems of controlling the difference between the largest and smallest measurements in a group of k items are not confined to situations involving temporal variability. Balance may require that a set of k objects not show too great a range in weight; flatness or straightness may require that a set of k items not vary too much in thickness or length; appearance may depend upon the range of variation within sets of k rather than upon some other type of variability.

2. METHOD OF SOLUTION

It is clear that when acceptance inspection is based on samples, there is always a risk that when good lots are offered they will be rejected, or that when bad lots are offered they will be accepted. The former risk depends on the frequency with which good lots yield bad samples, and the latter on the frequency with which bad lots yield good samples. These frequencies can be made as low as we please by taking sufficiently large samples and choosing the acceptance criterion properly, but they

cannot be eliminated except by complete inspection of the lot. Following established usage, we shall call the first kind of risk the "producer's risk" and the second kind the "consumer's risk."

For concreteness, let us assume that a lot of acceptable quality is defined as one in which the probability is at least $p_1 = 0.99$ that the range of 14 items selected at random will be less than 0.3, measured in whatever units are appropriate. Let us suppose further that the producer's risk is to be a small quantity, say $\alpha = 0.01$; that is to say, if lots of quality p_1 are offered we wish to reject them, on the average, no oftener than 1 time in 100. Suppose that a lot is unacceptable if the probability is $p_2 = 0.85$, or less, that the range of 14 items selected at random will be less than 0.3; and that the consumer's risk—the probability of accepting a lot of quality p_2 or worse if offered—is to be at most $\beta = 0.01$. Finally, let us assume that the distribution of the quality characteristic is adequately represented by a normal distribution.*

For a normal distribution the probability that the range of k independent observations is less than some preassigned number U depends only on the standard deviation σ . Thus, the criteria of acceptable and unacceptable lots, which were expressed above in terms of the proportion of the ranges of sets of 14 that are less than 0.3, can be expressed in terms of the lot standard deviation σ . It follows that the acceptance-inspection plan can be formulated in terms of the sample standard deviation, or, as proves to be more convenient in practice, in terms of the sum and the sum of squares of the observations. This reformulation of the definition of an acceptable lot permits a great gain in the efficiency of the inspection plan; for in using the sum of squared deviations as a measure of acceptability we make full use of the information provided by inspection of the sample, rather than of just that portion of the information given by selecting the extreme individuals in each group of 14 observations.

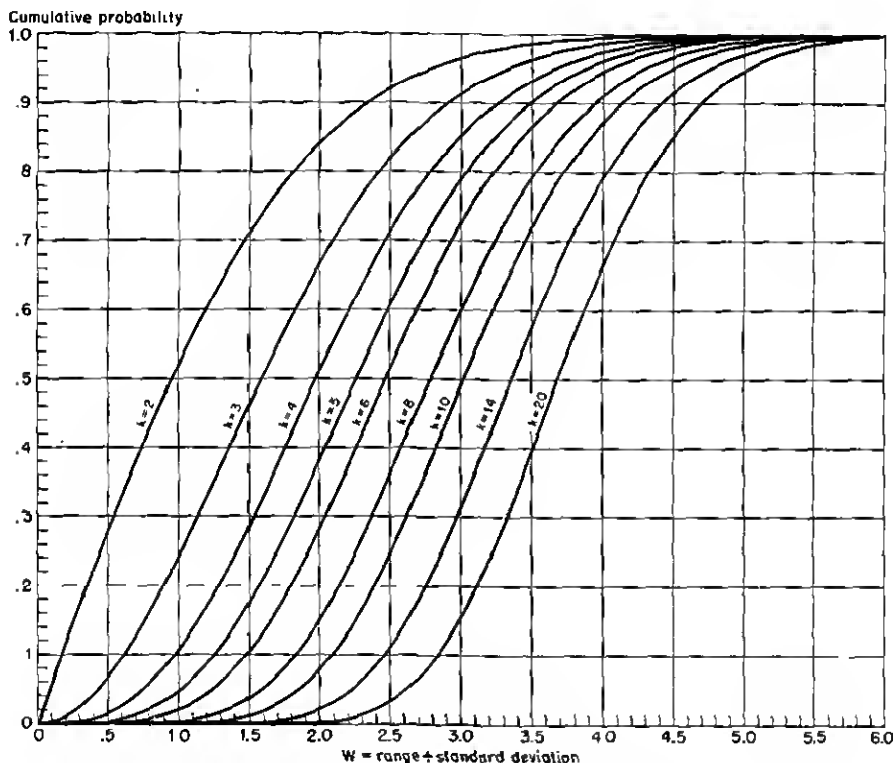
Let σ_1 be the value of the lot standard deviation that defines good quality. Then σ_1 depends on the group size k , on the acceptable value U of the range in groups of k , and on the proportion of ranges that can be allowed to exceed U . These three quantities are related to σ_1 through the cumulative distribution of the standardized range, which gives the probability that the range R_k of k items from a normal distribution will exceed any specified multiple W_k of the population standard deviation σ . Tables of the cumulative distribution of the range have been published by Pearson.† In Fig. 5.1, which is based on Pearson's

* If the assumption of normality is not justified, the inspection can be carried out on an attributes basis, by classifying each group of 14 in the sample as satisfactory or not.

† Pearson's table gives cumulative probabilities to 4 decimal places for values of k

tables, the vertical axis shows the probability that R_k/σ will exceed the values of W shown on the horizontal axis, and the various curves correspond with various group sizes k . For our purposes, R is given, W is obtained from Pearson's table or from Fig. 5.1, and σ is the quotient

$$\sigma = \frac{R_k}{W_k} \quad (1)$$



Data for these curves are from E. S. Pearson, *Biometrika*, 1942.—

FIG. 5.1.—Cumulative probability distribution of the range in samples of k from a normal population.

For the illustration cited, we find the value of W_{14} corresponding with probabilities of 0.99 and 0.85 on the curve for $k = 14$. These are 5.40 and 4.20, respectively; on substituting them and $R_k = 0.3$ into (1), we find $1/18$ and $1/14$ as the values of σ_1 and σ_2 .

Thus the problem becomes that of devising an inspection procedure for the standard deviation such that the operating-characteristic curve passes through the two points

(in his notation n) from 2 to 20 by steps of 1 and for values of W from 0 to 7.25 by steps of 0.01.

$$\sigma_1 = 0.05556 \quad L_{\alpha_1} = 0.99 \quad (2)$$

$$\sigma_2 = 0.07143 \quad L_{\alpha_2} = 0.01 \quad (3)$$

Such an inspection procedure may be carried out by either single or sequential sampling. The solutions are indicated only briefly here.*

3. SINGLE SAMPLING

To determine the required sample size, we compute†

$$\rho = \left(\frac{\sigma_2}{\sigma_1} \right)^2 = 1.6531 \quad (4)$$

Then in a table of χ^2 we find the number of degrees of freedom n for which

$$\frac{\chi_\alpha^2}{\chi_{1-\beta}^2} = \rho \quad (5)$$

where χ_α^2 denotes the value of χ^2 exceeded with probability α .

In the present example, since $\alpha = \beta = 0.01$, we may refer to Table 8.2 and seek 1.6531 in the column for $\beta = 0.01$; however, the table shows only that $n > 120$. We therefore use the large sample approximation‡

$$n = \frac{1}{2} \left(\frac{K_\alpha \sigma_1 + K_\beta \sigma_2}{\sigma_2 - \sigma_1} \right)^2 = 173 \quad (6)$$

where K_α and K_β represent normal deviates exceeded with probabilities α and β , respectively, which may be found from Table 1.1 in Chap. 1. Thus 173 is the number of degrees of freedom required, and since the mean is unknown the required sample size is

$$N = n + 1 = 174 \quad (7)$$

From the sample of 174, we calculate

$$S = \sum_{i=1}^N x_i^2 - \frac{(\sum x_i)^2}{N} \quad (8)$$

where x_i ($i = 1, 2, \dots, N$) represents the value of the i th measurement in the sample. The lot is rejected if $S > S_0$, where

$$S_0 = \sigma_1^2 \chi_\alpha^2(n) \quad (9)$$

* For a discussion of tests of the standard deviation see, on single sampling, Chap. 8, and, on sequential sampling, Chap. 17 below and Statistical Research Group, *Sequential Analysis*, Sec. 6.

† See Chap. 8, Sec. 2.4, especially Example III, pp. 272-274.

‡ See Chap. 8, Sec. 2.4, first footnote on p. 274.

in which $\chi^2_\alpha(n)$ represents the value of χ^2 for $n(= N - 1)$ degrees of freedom exceeded with probability α ; otherwise the lot is accepted. In the present example, n is outside the range of the χ^2 tables, so we use the approximation (due to R. A. Fisher)

$$\begin{aligned}\chi^2_\alpha(n) &= \frac{(K_\alpha + \sqrt{2n - 1})^2}{2} \\ &= 218.416\end{aligned}\quad (10)$$

The OC curve is easily obtained from the fact that the probability L_σ of accepting a lot of quality σ when offered is simply the probability that a value of χ^2 based on n degrees of freedom will be less than S_0/σ^2 . When $\alpha = 0.01$ or 0.05 and n does not exceed 120, Table 8.1 or 8.2 provides 13 points on the OC curve; values of σ^2/σ_1^2 are shown for various values of L_σ . When n is beyond the range of the table, the OC curve can be found from

$$\sigma = \frac{(K_\alpha + \sqrt{2n})\sigma_1}{\sqrt{2n} - K_{L_\sigma}} \quad (11)$$

4. SEQUENTIAL SAMPLING

A sequential-inspection plan based on standard deviations is defined by two parallel straight lines given by the formulas

$$Z_n = h_2 + sn \quad (\text{rejection line}) \quad (12)$$

$$Z_n = -h_1 + sn \quad (\text{acceptance line}) \quad (13)$$

where h_1 , h_2 , and s are positive, n represents one less than the number of observations taken sequentially, and

$$Z_n = \sum_{i=1}^{n+1} x_i^2 - \frac{(\sum x_i)^2}{n+1}$$

is the sum of squares of deviations of the $n + 1$ observations from their mean.

The sequential procedure is as follows: Draw the two parallel lines given by equations (12) and (13) with Z_n on the vertical scale and n on the horizontal scale. Start taking observations, beginning with two observations and thereafter adding one observation at a time. After each observation compute Z_n from all observations and plot its value against the corresponding value of n (which is one less than the total number of observations thus far taken). If at any stage the plotted point falls on or above the upper line, given by equation (12), reject the lot; if it falls on or below the lower line, given by equation (13), accept the lot. If, however, the plotted point falls between the two parallel lines, take another observation. Continue this process until a decision of acceptance or rejection is reached.

The two intercepts $-h_1$ and h_2 and the common slope s , which determine the two parallel lines, are given by

$$h_1 = \frac{2 \log_e \frac{1-\alpha}{\beta}}{\frac{1}{\sigma_1^2} - \frac{1}{\sigma_2^2}} \quad (14)$$

$$= 0.071799$$

$$h_2 = \frac{2 \log_e \frac{1-\beta}{\alpha}}{\frac{1}{\sigma_1^2} - \frac{1}{\sigma_2^2}} \quad (15)$$

$$= 0.71799$$

and

$$s = \frac{\log_e \frac{\sigma_2^2}{\sigma_1^2}}{\frac{1}{\sigma_1^2} - \frac{1}{\sigma_2^2}} \quad (16)$$

$$= 0.0039268$$

The OC curve for the sequential plan is computed from the following formulas:

$$\sigma = \sqrt{\frac{1 - e^{-2ts}}{2t}} \quad L_s = \frac{e^{t(h_1+h_2)} - e^{th_1}}{e^{t(h_1+h_2)} - 1} \quad (17)$$

It will be observed that L_s , the ordinate of the OC curve, is not given directly as a function of σ , but parametrically through a third variable t in terms of which σ is also defined. The OC curve for this example is shown in Fig. 5.2.

The average sample number (ASN) curve shows the relationship between the standard deviation in the submitted lot and the average number of items that will be inspected before a decision is reached. The ordinate \bar{N}_s of the ASN curve, corresponding to the abscissa σ , is given by

$$\bar{N}_s = \frac{L_s(h_1 + h_2) - h_2}{s - \sigma^2} + 1 \quad (18)$$

where L_s and σ are given by equations (17). Formula (18) can be evaluated directly for every value of σ except $\sigma = \sqrt{s}$, for which it can be shown that

$$\bar{N}_{\sqrt{s}} = \frac{h_1 h_2}{2s^2} + 1 \quad (19)$$

This will ordinarily be close to the maximum average amount of inspection required to reach a decision. The ASN curve for the present example is included in Fig. 5.2.

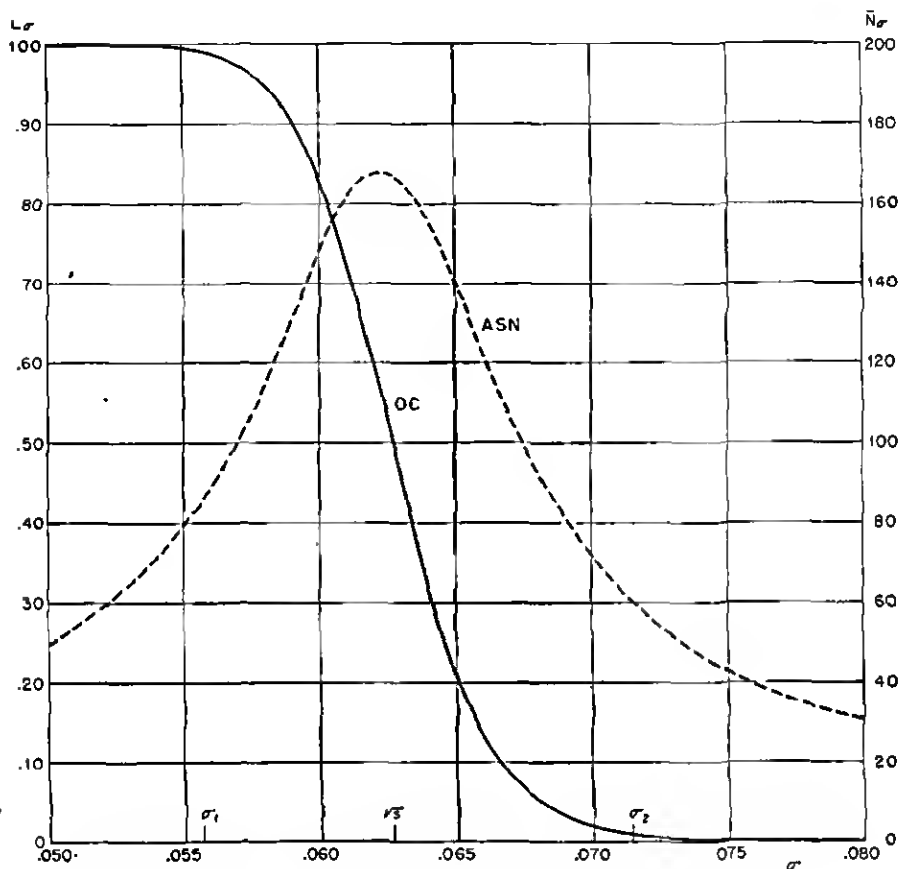


FIG. 5.2.—OC and ASN curves for sequential-sampling plan based on standard deviation; $\sigma_1 = 0.05556$, $\sigma_2 = 0.07143$, $\alpha = 0.01$, $\beta = 0.01$; $h_1 = 0.07180$, $h_2 = 0.07180$, $s = 0.003927$.

5. REFERENCES

- FISHER, RONALD A., and YATES, FRANK: *Statistical Tables for Biological, Agricultural, and Medical Research*, 2d ed., Oliver and Boyd, Ltd., London and Edinburgh, 1943, 98 + viii pp.
- PEARSON, E. S.: "The Probability Integral of the Range in Samples of n Observations from a Normal Population," *Biometrika*, Vol. 32 (1942), pp. 301-308.
- Statistical Research Group, Columbia University: *Sampling Inspection*, McGraw-Hill Book Company, Inc., New York, 1947.
- Statistical Research Group, Columbia University: *Sequential Analysis of Statistical Data: Applications*, rev. ed., Columbia University Press, New York, 1945.
- THOMPSON, CATHERINE M.: "Table of Percentage Points of the χ^2 Distribution," *Biometrika*, Vol. 32 (1941), pp. 187-191.
- TIPPETT, L. H. C.: "The Distribution of the Extreme Individuals and of the Range in Samples from a Normal Population," *Biometrika*, Vol. 17 (1925), pp. 364-387; *Tables for Statisticians and Biometricians*, Part II, Table XXII, pp. 165-166.

CHAPTER 6

VARIABILITY OF AMOUNT OF INSPECTION FOR DOUBLE, MULTIPLE, AND SEQUENTIAL SAMPLING

	PAGE
1. Single, Double, Multiple, and Sequential Sampling	237
2. Variability of Amount of Inspection.	238
3. Illustrations	238
4. Computational Methods.	244
5. References.	244

FIGURES

6.1 ASN Curves for Double, Multiple, and Sequential Plans of Table 6.1 . . .	240
6.2 $\sigma(N)$ Curves for Double, Multiple, and Sequential Plans of Table 6.1 . . .	241
6.3 ASN Curves for Double, Multiple, and Sequential Plans of Table 6.2 . . .	242
6.4 $\sigma(N)$ Curves for Double, Multiple, and Sequential Plans of Table 6.2 . . .	243

TABLES

6.1 Double, Multiple, and Sequential Plans of Example I	239
6.2 Double, Multiple, and Sequential Plans of Example II.	244

This chapter was prepared by the editors
from more extensive material prepared by
Myra Levine, Socony Vacuum Oil Company

CHAPTER 6

VARIABILITY OF AMOUNT OF INSPECTION FOR DOUBLE, MULTIPLE, AND SEQUENTIAL SAMPLING

1. SINGLE, DOUBLE, MULTIPLE, AND SEQUENTIAL SAMPLING

Sampling inspection is said to be based on attributes if inspection of each item results in its classification as defective or nondefective, and disposition of the lot or process from which the sample comes depends upon the number of defectives found in the sample. One or more samples are selected at random from the lot; if the total number of defectives found in the first k samples does not exceed an acceptance number A_k , the lot is accepted; if it equals or exceeds a rejection number R_k ($R_k > A_k$), the lot is rejected; if it falls between A_k and R_k , another sample is inspected.

A single-sampling plan is one for which

$$R_1 = A_1 + 1 \quad (1)$$

A double-sampling plan is one for which

$$\begin{aligned} R_1 &> A_1 + 1 \\ R_2 &= A_2 + 1 \end{aligned} \quad (2)$$

A multiple-sampling plan is one for which

$$\begin{aligned} R_k &> A_k + 1 && \text{for } k \leq 2 \\ R_k &= A_k + 1 && \text{for some } k > 2 \end{aligned} \quad (3)$$

In a sequential-sampling plan, the successive samples are all of size 1 and

$$R_k - A_k = C + \delta_k \quad (4)$$

where C is some constant and each δ_k is 0 or 1.*

* For an exposition of single, double, and multiple sampling, see Statistical Research Group, *Sampling Inspection*; what is here called "multiple sampling" is there called "sequential sampling," and what is here called "sequential sampling" is there called "item-by-item sequential sampling." For an exposition of sequential sampling see Chap. 17 of this volume, or Statistical Research Group, *Sequential Analysis*. (For full citations, see Sec. 5.)

Equation (4) is a necessary condition for a sequential-sampling plan, but it is not quite a sufficient condition unless further conditions are imposed on the δ_k .

2. VARIABILITY OF AMOUNT OF INSPECTION

One of several factors determining the relative merits of single, double, multiple, and sequential sampling is the variability of the amount of inspection for plans giving equivalent operating-characteristic (OC) curves. Variability of the amount of inspection causes fluctuations in the inspection load and thus may create administrative problems in an inspection program.

Variability may be interpreted in two ways. First, it may mean variation in the average number of items inspected per lot as the quality of submitted lots varies; in other words, the amplitude of the rise and fall of the average sample number (ASN) curve. Second, it may mean variation in the number of items inspected for lots of a given quality.

Clearly, single sampling will show less variability, in either sense, than double, multiple, or sequential sampling. In fact, with single sampling there will be no variability of either kind unless inspection is curtailed, that is, terminated as soon as the rejection number is exceeded or the number of items remaining uninspected is insufficient to cause rejection even if all are defective.

No general relations among the variabilities of double, multiple, and sequential plans are known. The purpose of this chapter is to present two illustrative comparisons. These two comparisons suggest by their differences that no simple conclusions about the relative variability of the three types of sampling are valid. In the illustrations it is assumed that the first sample of the double and multiple plans will be inspected completely (this being usual* to facilitate estimation of the process average), that inspection of later samples will be curtailed as soon as the rejection number is reached, but that curtailing will not be applied to accepted lots.

3. ILLUSTRATIONS

Example I. Table 6.1 presents a set of double, multiple, and sequential plans whose OC curves are nearly the same.† Figure 6.1 shows their average sample numbers \bar{N} as functions of lot quality, and Fig. 6.2 shows their standard deviations $\sigma(N)$ of amount of inspection for lots of a given quality as functions of lot quality.

Example II. Table 6.2 presents a second set of plans with matching OC curves;‡ Fig. 6.3 shows \bar{N} as a function of lot quality, and Fig. 6.4 shows $\sigma(N)$ as a function of lot quality.

* It is not, however, necessary. See GIRSHICK, MOSTELLER, and SAVAGE, "Unbiased Estimates for Certain Binomial Sampling Problems with Applications."

† The OC curves of the double and multiple plans are shown in Table 4 of *Sampling Inspection* for sample size letter H, acceptable quality level (AQL) class 0.32–0.65 percent defective (p. 288).

‡ The OC curves of the double and multiple plans are shown in Table 4 of *Sampling Inspection* for sample size letter K, AQL class 3.2–4.4 percent defective (p. 330).

TABLE 6.1
DOUBLE, MULTIPLE, AND SEQUENTIAL PLANS OF EXAMPLE I

DOUBLE SAMPLING

Sample	Sample size	Combined samples		
		Size	Acceptance number	Rejection number
First.....	50	50	0	3
Second.....	100	150	2	3

MULTIPLE SAMPLING

Sample	Sample size	Combined samples		
		Size	Acceptance number	Rejection number
First.....	20	20	*	2
Second.....	20	40	*	2
Third.....	20	60	0	2
Fourth.....	20	80	1	3
Fifth.....	20	100	1	3
Sixth.....	20	120	1	3
Seventh.....	20	140	2	3

* Acceptance not permitted until three samples have been inspected.

SEQUENTIAL SAMPLING

$$\alpha = 0.05 \quad \beta = 0.10 \quad p_1 = 0.005 \quad p_2 = 0.05$$

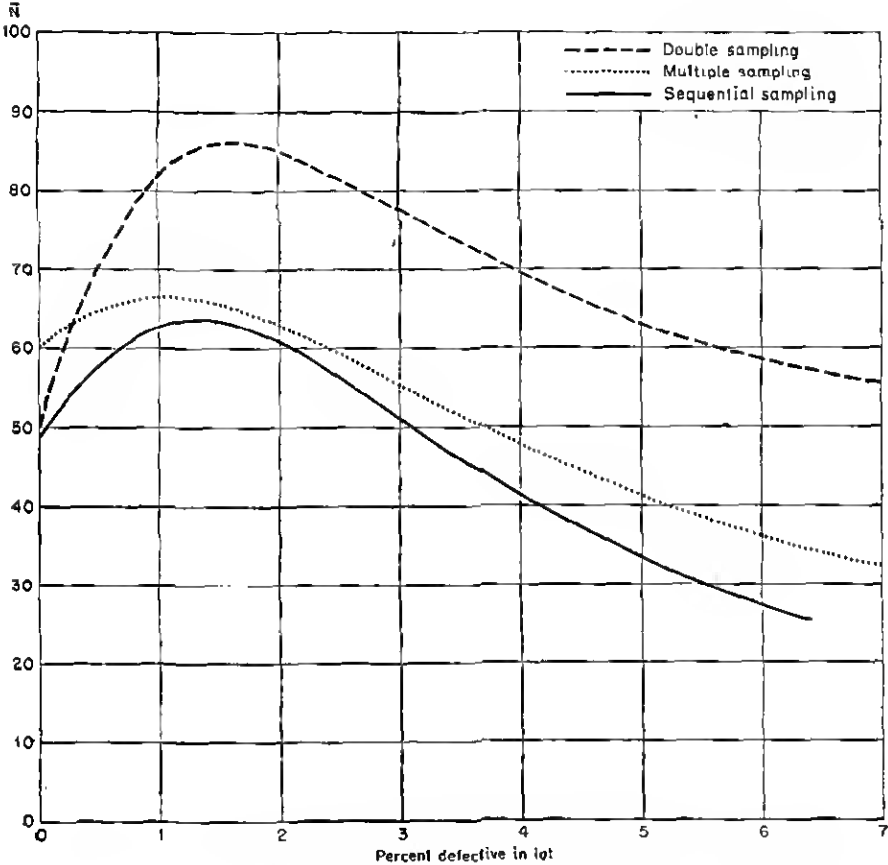


FIG. 6.1.—ASN curves for double, multiple, and sequential plans of Table 6.1.

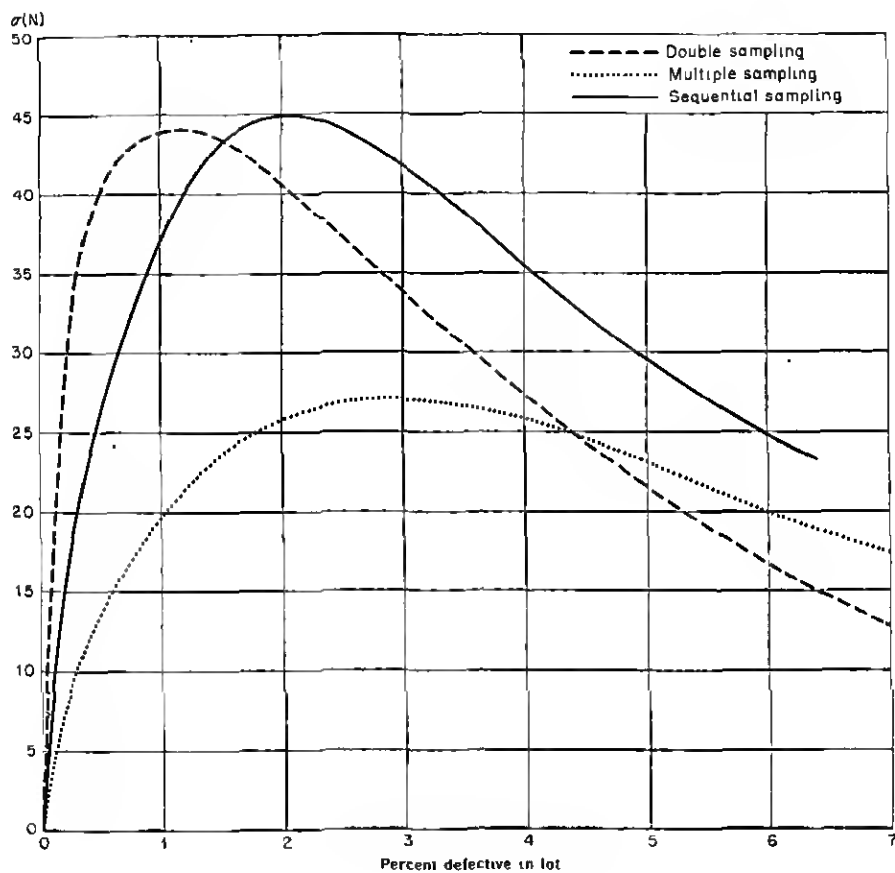


FIG. 6.2.— $\sigma(N)$ curves for double, multiple, and sequential plans of Table 6.1.

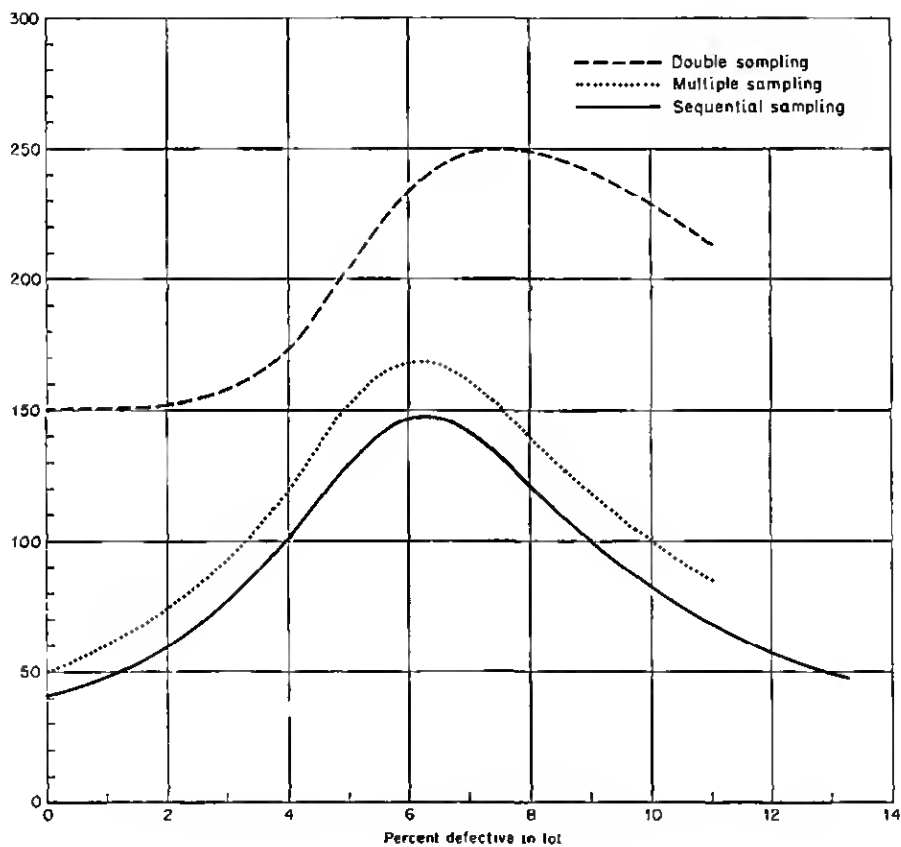


FIG. 6.3.—ASN curves for double, multiple, and sequential plans of Table 6.2.

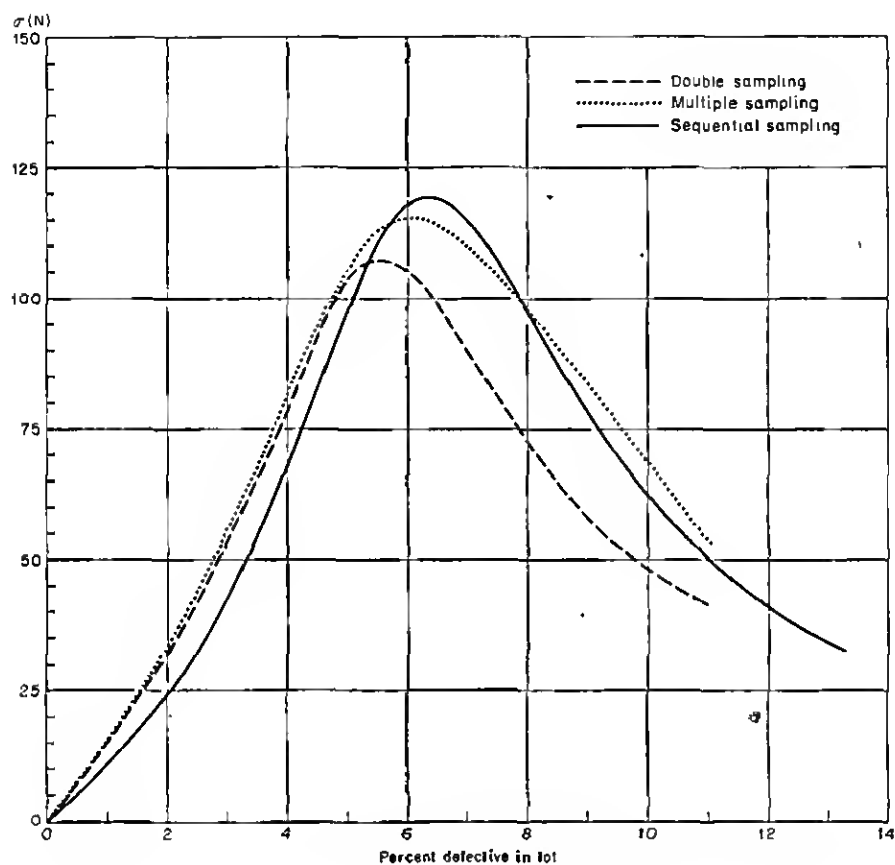


FIG. 6.4.— $\sigma(N)$ curves for double, multiple, and sequential plans of Table 6.2.

TABLE 6.2
DOUBLE, MULTIPLE, AND SEQUENTIAL PLANS OF EXAMPLE II
DOUBLE SAMPLING

Sample	Sample size	Combined samples		
		Size	Acceptance number	Rejection number
First.....	150	150	9	24
Second.....	300	450	23	24

MULTIPLE SAMPLING

Sample	Sample size	Combined samples		
		Size	Acceptance number	Rejection number
First	50	50	1	6
Second.	50	100	3	9
Third.....	50	150	7	13
Fourth.....	50	200	10	16
Fifth.....	50	250	13	10
Sixth.....	50	300	16	22
Seventh.....	50	350	19	25
Eighth.....	50	400	24	25

SEQUENTIAL SAMPLING

$$\alpha = 0.05 \quad \beta = 0.10 \quad p_1 = 0.0410 \quad p_2 = 0.0920$$

4. COMPUTATIONAL METHODS

For double and multiple sampling, \bar{N} and $\sigma(N)$ may be calculated by an extension of methods described in *Sampling Inspection*, Chap. 17. For sequential sampling, the computations for $\bar{N} = E(N)$ are based on the formula derived in *Sequential Analysis*, Sec. B.0921, and those for $\sigma(N)$ on the relation

$$\sigma^2(N) = E(N^2) - [E(N)]^2 \quad (5)$$

where the formula for $E(N^2)$ may be obtained by an extension of the method used in Sec. B.0921 of *Sequential Analysis* for obtaining $E(N)$.

5. REFERENCES

- GIRSHICK, M. A., MOSTELLER, F., and SAYAOE, L. J.: "Unbiased Estimates for Certain Binomial Sampling Problems with Applications," *Annals of Mathematical Statistics*, Vol. 17 (1946), pp. 13-23.
- Statistical Research Group, Columbia University: *Sampling Inspection*, McGraw-Hill Book Company, Inc., New York, 1947.
- : *Sequential Analysis of Statistical Data: Applications*, rev. ed., Columbia University Press, New York, 1945.

Part II

PLANNING EXPERIMENTS

	PAGE
Chapter 7. Planning and Analyzing Experiments for Comparing Two Percentages	247
Chapter 8. Planning and Interpreting Experiments for Comparing Two Standard Deviations	267
Chapter 9. Utilization of Limited Experimental Facilities When the Cost of Each Measurement Depends on Its Magnitude	319
Chapter 10. Experiments in Which the Independent Variable Is Known Only in Terms of a Probability Distribution	329
Chapter 11. Planning an Experiment for Estimating the Mean and Standard Deviation of a Normal Distribution from Observations on the Cumulative Distribution	339
Chapter 12. Abandoning an Experiment Prior to Completion	353
Chapter 13. Planning Experiments Seeking Maxima	363

CHAPTER 7 PLANNING AND ANALYZING EXPERIMENTS FOR COMPARING TWO PERCENTAGES

	PAGE
1. Type of Problem.	249
2. Method of Analysis.	250
2.1 Exact Method	250
2.2 Short-cut Methods	253
2.3 Alternative Methods	255
3. Necessary Number of Trials	258
4. Operating Characteristics	261
5. Technical Notes	262
6. References.	265

FIGURES

7.1 Number of Cases Required for Comparing Two Percentages	260
7.2 Operating-characteristic Curve for a Comparison of Two Percentages, $N^* = 500, K_\alpha = 1.045$	262

This chapter was prepared by
Edward Paulson, *University of North Carolina*
W. Allen Wallis, *University of Chicago*

CHAPTER 7

PLANNING AND ANALYZING EXPERIMENTS FOR COMPARING TWO PERCENTAGES

1. TYPE OF PROBLEM

The type of problem dealt with in this chapter may be indicated by a simple example. Suppose that trials of two fire-control devices have resulted in the following data:

TABLE 7.1

	Hits	Misses	Total
Old.	3	197	200
New.	4	196	200
Total.	7	393	400

The question is whether the new method, which shows 33 percent more hits than the old, can be expected to yield more hits in the long run; or whether its superiority in this experiment ought to be regarded as mere chance, in the sense that two series of trials with the same method would often differ as much.

We may look at the question this way: From 400 rounds, 7 hits were secured. If the two methods are really equally good in the long run, these 7 hits should be divided between the two series in proportion to the total numbers in the series, except for chance variations. In the present case we should expect the 7 hits to be divided equally between the two series; and similarly the 393 misses. As it happens, the division in Table 7.1 is as nearly equal as it possibly could be, since the entries are necessarily integers. It is therefore immediately obvious in this particular instance that the probability is one-half that, if the two methods were really equally good in the long run, a single experiment would show for the new method as much (or more) apparent superiority as is shown in Table 7.1. (If this is not obvious, it can be verified by the method described below for use with cases where the answer is not apparent.)

Data such as those of Table 7.1 represent a double dichotomy. The observations are dichotomized according to one criterion—that is, they are divided into two mutually exclusive and exhaustive classes—and then each class is dichotomized again according to a second criterion.

The result of doubly dichotomizing the data is, of course, the same whichever criterion is applied first; that is, we may regard the data as classified first by method (old or new) and then by effect (hit or miss), or we may regard them as classified first by effect and then by method. The marginal totals of Table 7.1 represent two independent dichotomies of the data; they do not constitute a double dichotomy. The problem may be put in either of two ways: (1) Is the division between effects the same for both methods? (2) Is the division between methods the same for both effects? These questions are logically identical, though for a particular problem one of them usually seems more natural than the other. The problem is thus to test the homogeneity of a pair of dichotomies.

2. METHOD OF ANALYSIS*

2.1. Exact Method

In order to illustrate the general procedure for testing the homogeneity of a double dichotomy such as that of Table 7.1, consider the data of Table 7.2, where the answer is not immediately apparent.

TABLE 7.2

	Successes	Failures	Total
Standard	2	198	200
Experimental	5	195	200
Total	7	393	400

For convenience and generality the two methods compared are here designated "standard" and "experimental" and the two possible outcomes of a trial with either method as "success" and "failure." In practice, of course, the two methods may be equally experimental or equally standard, and the two possible outcomes may be two types of success or two types of failure or merely two different outcomes not properly regarded as either success or failure.

It might appear, in view of the remarks in Sec. 1, that we could treat the 2:5 division of successes like a 2:5 division of heads and tails on 7 tosses of a coin, using the binomial distribution to find the probability of as many as 5 heads on 7 tosses if the coin were really unbiased. Table 7.2, unlike Table 7.1, however, gives different answers for the successes and failures columns according to this treatment; so some other method of analysis is called for. (In this particular instance, however, it happens that analysis of the seven successes according to a binomial distribution gives an excellent approximation to the correct probability, because both proportions of successes are small; see below, Sec. 2.2, p. 255.)

We proceed as follows. Let P designate the true long-run probability

* See FISHER, *Statistical Methods*, Secs. 21, 21.01, and 21.02. (For full citations, see Sec. 6.)

of a success, that is, the probability of a success in the population from which the sample comes. P , of course, is unknown, for we should have to carry out an infinitely long series of trials to measure it. But we make our calculations on the assumption that P is the same in both series, and, as we shall see, it cancels out. If, on the assumption that P is really the same in the long run for both series, we find that a difference as great as that shown in the data would be unlikely, then the fact that this unlikely difference has actually been observed experimentally leads us to conclude that the assumption was wrong—to conclude, in other words, that the long-run probabilities are not equal.

The probability that 200 trials will show exactly 2 successes is, by the binomial distribution,

$$\frac{200!}{2!198!} P^2(1 - P)^{198} \quad (1)$$

Similarly, the probability of exactly 5 successes is

$$\frac{200!}{5!195!} P^5(1 - P)^{195} \quad (2)$$

So the probability that the two series of 200 trials will show exactly 2 successes for the first series and exactly 5 for the second is the product of (1) and (2)

$$\frac{200!200!}{2!5!195!198!} P^7(1 - P)^{393} \quad (3)$$

This is an absolute probability, whereas we require the conditional probability that if exactly 7 successes and 393 failures occur in the two series they will be divided between the series as shown in Table 7.2; hence (3) must be divided by the probability of exactly 7 successes in 400 trials.

$$\frac{400!}{7!393!} P^7(1 - P)^{393} \quad (4)$$

The probability that if we get 7 successes among two series of 200 each, they will be distributed 2 to the standard method and 5 to the experimental, is the ratio of (3) to (4), or

$$\frac{7!393!200!200!}{400!2!5!195!198!} = 0.1636 \quad (5)$$

It should be noted that expression (5) would be the same if expressions (1), (2), and (4) had been formed from the two columns instead of from the two rows of Table 7.2.

In general, expression (5) is composed as follows: The numerator is the product of the factorials of the four marginal totals; the denominator is the product of the factorials of the four cell entries and the factorial

of their sum. Thus, if we give Tables 7.1 and 7.2 the general representation shown in Table 7.3,

TABLE 7.3

	Successes	Failures	Total
Standard.	a	b	$a + b$
Experimental.	c	d	$c + d$
Total.	$a + c$	$b + d$	$a + b + c + d$

expression (5) may be written

$$\frac{(a + b)!(c + d)!(a + c)!(b + d)!}{a!b!c!d!(a + b + c + d)!} \quad (6)$$

Expression (5) gives the probability that if in fact the long-run probabilities were equal, an experiment involving 200 trials of each method and resulting in a total of 7 successes would show exactly the superiority for the experimental method that is shown by Table 7.2. For the final probability to use in judging whether there is a long-run difference, we must add to (5) the probabilities of superiorities greater than that of Table 7.2. Tables 7.4 and 7.5 show possible results that would have indicated even greater superiority for the experimental method than does Table 7.2.

TABLE 7.4

	Successes	Failures	Total
Standard.	1	199	200
Experimental.	6	194	200
Total	7	393	400

Expression (6) gives the probability for Table 7.4 as

$$\frac{7!393!200!200!}{400!1!6!194!199!} = 0.0534 \quad (7)$$

TABLE 7.5

	Successes	Failures	Total
Standard.	0	200	200
Experimental.	7	193	200
Total.	7	393	400

Expression (6) gives the probability for Table 7.5 as

$$\frac{7!393!200!200!}{400!0!7!193!200!} = 0.0074 \quad (8)$$

The sum of the three probabilities (5), (7), and (8), or 0.2244, is the probability that the experiment will show as much or more apparent superiority of the experimental method as Table 7.2 shows, if in fact there is no real difference. It should be noted that we add together the probabilities of only those cases representing greater superiority for the experimental method than was observed in the sample. We do not include the probabilities of cases representing greater superiority for the standard than was observed for the experimental method. This is because we are analyzing the data in order to decide whether the experimental is superior to the standard method, not simply to decide whether there is a difference between the methods without regard to its direction.

Finally, a conclusion is reached regarding the superiority of the experimental method as follows: We agree to accept the experimental method as superior to the standard on the basis of an analysis of the above type only when the resulting probability is less than α , where α is chosen in advance and is generally taken to be 0.10, 0.05, 0.01, or 0.001, depending upon the seriousness of accepting the experimental method as superior when it is not. Then α is the probability of accepting the experimental method as superior when actually there is no real difference between the methods. In terms of any of the usual values of α , the probability 0.2244 would imply that the data of Table 7.2 provide no basis for concluding that the experimental method is actually superior to the standard.

2.2. Short-cut Methods

The evaluation of the factorials involved in expressions (5), (7), and (8) was done by cancellation of common factors. This procedure is the simplest in this case, but in general it may be very laborious. The calculations can be considerably reduced by using a table of the logarithms of factorials.*

A much simpler procedure, which usually yields very satisfactory approximations to the exact method described in Sec. 2.1, is available when at least two (and preferably five) successes would be expected in each cell if there were no difference in the long-run probabilities for the two methods. This expected number of successes is computed for any cell by dividing the product of the marginal totals for that cell by the total number of trials made; thus, the expected number of successes for the standard method is, on the basis of Table 7.3,

$$\frac{(a + b)(a + c)}{a + b + c + d} \quad (9)$$

* A convenient table is given in Fry, *Probability and Its Engineering Uses*. Shorter tables can be found in various handbooks.

In such cases we calculate a quantity χ_c as follows:

First, adjust the table of observations so that each frequency is brought $\frac{1}{2}$ unit nearer the frequency expected if there were no long-run difference between the two methods. This may be done by adjusting one frequency and then changing the others so that the marginal totals of the new table equal those of the old. For example, in Table 7.2 the expected frequency for the first cell is $\frac{7 \times 200}{400} = 3\frac{1}{2}$, so we increase the observed figure of 2 to $2\frac{1}{2}$. Changing the other figures to keep the marginal totals fixed, we have

TABLE 7.6

	Successes	Failures	Total
Standard.	$2\frac{1}{2}$	$197\frac{1}{2}$	200
Experimental	$4\frac{1}{2}$	$195\frac{1}{2}$	200
Total.	7	393	400

Table 7.6 represents Table 7.2 "corrected for continuity."*

Second, each adjusted frequency is subtracted from the corresponding expected frequency, the differences are squared, the squares are divided by the corresponding expected frequencies, and the ratios are summed to obtain χ_c^2 .

The final value* of χ_c^2 may be obtained directly without going through the intermediate steps, as follows: Calculate the products of frequencies diagonally opposite each other in the adjusted table; subtract one diagonal product from the other; square the difference; multiply the square by the sum of the four frequencies in the table; and divide this product by the product of all four marginal totals. From the data of Table 7.6, we have

$$\chi_c^2 = \frac{(2\frac{1}{2} \times 195\frac{1}{2} - 4\frac{1}{2} \times 197\frac{1}{2})^2 \times 400}{7 \times 393 \times 200 \times 200} = 0.5816 \quad (10)$$

More generally, if we replace a , b , c , and d in Table 7.3 by a' , b' , c' , and d' , representing the frequencies corrected for continuity, (10) becomes

$$\chi_c^2 = \frac{(a'd' - b'c')^2(a + b + c + d)}{(a + b)(a + c)(c + d)(b + d)} \quad (11)$$

* Although this account of the continuity correction describes the procedure accurately, it may convey an erroneous idea of the theoretical basis for the correction. The general procedure is to carry through the calculation of χ from the original data, then find the next lowest value of χ that could have arisen, and finally take χ_c as halfway between these two values. In the particular case of double dichotomies, this value of χ can be found most easily by correcting the original data as in Table 7.6; but in most other cases where the χ test is used, correction of the original data will lead to serious error in the value of χ . For an excellent analysis and presentation of this point, see Cochran, "The χ^2 Correction for Continuity," especially p. 423.

Next, we take the square root and find $\chi_e = 0.7626$. This may be treated as a normal deviate; that is, the required probability is given by

$$\frac{1}{\sqrt{2\pi}} \int_{\chi_e}^{\infty} e^{-\frac{1}{2}t^2} dt \quad (12)$$

Referring to a table of the normal probability integral,* for example Table 1.5 of Chap. 1, we find the probability to be 0.2228. This compares favorably with the exact probability of 0.2244 found in Sec. 2.1.

More accurate values of χ_e corresponding to the probabilities 0.025 and 0.005 than are implied by (12) are given in Table VIII, "Tests of Significance for 2×2 Contingency Tables," in Fisher and Yates, *Statistical Tables*. Detailed instructions and illustrations for the use of this table are given in its introduction.

When the percentage of successes is small and the number of trials in each series large, as is the case in the examples discussed here, the successes may be analyzed by the binomial distribution, along the lines discussed in Sec. 1 and the second paragraph of Sec. 2.1.† The value of P for the binomial test is the proportion of all trials that fall into, say, the standard series. In the illustration of Table 7.2, $P = \frac{1}{2}$. According to the binomial distribution, the probability that seven trials of an event having two equally likely outcomes will show as many as five or more of a designated type (in other words, the probability that with seven successes observed five or more will occur in the experimental series) is

$$\frac{1}{2^7} \left(\frac{7!}{2!5!} + \frac{7!}{1!6!} + \frac{7!}{0!7!} \right) = 0.2266 \quad (13)$$

This conforms satisfactorily to the exact value 0.2244 found in Sec. 2.1.

2.3. Alternative Methods

A procedure that has been widely used for testing the significance of the difference between two proportions is based on the following considerations: The difference between the two percentages is divided by the standard error of the difference, and the ratio is regarded as normally distributed. The standard error of the difference is computed from the familiar relation that the standard error of the difference between two independent statistical variables is the square root of the sum of the squared standard deviations of the two variables. The standard error of a proportion p is well known to be $\sqrt{P(1-P)/N}$,

* For a detailed table, see the tables prepared by the New York Mathematical Tables Project.

† See PRZYBOROWSKI and WILEŃSKI, "Homogeneity of Results in Testing Samples from Poisson Series," especially Sec. 2, Derivation of Test, pp. 314-317.

where P is the true population value of the proportion and N is the number of trials.

Applying these considerations, it is often concluded that

$$V = \frac{\sqrt{N}(p_E - p_S)}{\sqrt{p_S(1 - p_S) + p_E(1 - p_E)}} \quad (14)$$

where p_E is the observed proportion for the experimental method

p_S is the observed proportion for the standard method

N is the number of trials with *each* method

may be treated as normally distributed with mean of 0 and standard deviation of 1. If the probability of obtaining a normal deviate as large as V is small, it is concluded that the difference in the proportions is greater than can be ascribed to chance.

There are two serious objections to the procedure by which expression (14) is derived: (1) V will not actually be distributed as assumed; and (2) the procedure is not self-consistent.

With regard to the distribution of V , there are two considerations: In the first place, the true population standard deviation of the difference is required in the denominator if the ratio is to be normally distributed with unit variance when N is large; but actually only experimental values are available. Hence, chance variations affect not only the numerator but also the denominator of V . In the second place, even if we know the true standard deviation, the distribution of the difference ($p_E - p_S$) cannot be satisfactorily approximated by a normal distribution when the proportions are near 0 or 1, unless N is very large.

The procedure leading to expression (14) is inconsistent in two respects. It sets out to calculate the probability that, if there were actually no long-run difference, a difference as great as that observed would occur by chance. But if there were no long-run difference in the proportions, there would be none in the standard deviations. Therefore, when the standard deviation is estimated from the experiment, the estimate should be based on the two series together. This leads to considering

$$x = \frac{\sqrt{N}(p_E - p_S)}{\sqrt{(p_S + p_E)\left(1 - \frac{p_S + p_E}{2}\right)}} \quad (15)$$

as a normally distributed variable.

The second inconsistency in expression (14) may be seen as follows: It would be perfectly logical to find what proportion of the total successes were made with the standard method and what proportion of the total failures were made with the experimental method. These proportions should be equal if the standard and experimental methods are

equally effective. But if the significance of the difference of this pair of proportions is tested by expression (14), the result is not the same as when the logically equivalent pair based on methods is tested. Expression (15), however, is consistent in this respect as well as in the standard error it uses.

Expression (15) is mathematically identical with formula (11) in the previous section, except that formula (11) is calculated from the data corrected for continuity. Thus, in terms of the frequencies of Table 7.3 (without continuity corrections), expression (15) can be written as

$$x = \frac{\sqrt{a+b+c+d} (ad-bc)}{\sqrt{(a+b)(a+c)(b+d)(c+d)}} \quad (16)$$

with $a+b=c+d=N$. This is simply the square root of expression (11), neglecting the continuity corrections. When the continuity corrections are taken into account and N is introduced for simplification, expression (16) becomes

$$x_c = \frac{ad-bc+N}{\sqrt{(N/8)(a+c)(b+d)}} \quad (17)$$

Note that N in expressions (14), (15), (16), and (17) represents the number of trials in *each* set. Also note that (17) is valid only when the continuity corrections increase a and d and decrease b and c ; for the reverse situation, $+N$ in the numerator of (17) must be replaced by $-N$.

Expression (14), though it is theoretically inferior to expressions (15) and (17), does not differ materially from them when N is large. Since (15) and (17) are theoretically superior and are little or no more trouble to calculate, they are always preferable to (14). Even (15) and (17), however, are approximations; they fail for very small values of N or very small probabilities of a success, and in such cases the procedures outlined above in Secs. 2.1 and 2.2 must be used. The procedure of Secs. 2.1 and 2.2 should be used also when $a+b$ is different from $c+d$.

For practical work with double dichotomies, the Zubin Item Analyzer gives results essentially equivalent to those of expression (14).^{*} In this device the difficulties that (1) proportions are not normally distributed when the true proportion is small, and (2) the standard deviation depends upon the true proportion, are avoided by employing a new variable θ , which is a function of p . The function is chosen so that, first, θ is more nearly normally distributed than p , and second, the standard deviation of θ is independent of the true long-run value of θ or p . A

^{*} For a description of this device, see Fulcher and Zubin, "The Item Analyzer." A model constructed by Dr. Fulcher was lent to the Statistical Research Group for trial in 1943. It proved quick and easy to use and would be cheap to build, as it involves only plywood and celluloid.

function that meets these requirements when N is not too small is

$$\theta = 2 \arcsin \sqrt{p} \quad (18)$$

Unless N is very small, θ may be regarded as normally distributed; the standard deviation is $1/\sqrt{N}$ when θ is measured in radians or $57.3/\sqrt{N}$ when θ is measured in degrees. The Zubin Analyzer is a mechanical device for transforming the proportions to the proper angles and reading directly the difference $(\theta_E - \theta_S)$. The required probability can then be read from a simple chart showing the difference and its standard error, $\sqrt{2/N}$.*

3. NECESSARY NUMBER OF TRIALS

A method that is sometimes recommended for finding the required sample size in experiments involving double dichotomies is to set V in expression (14) equal to the value V_α , which would be exceeded only α percent of the time if there were no true differences in the proportions, and then solve for N , using values of p_S and p_E obtained experimentally. The result is

$$N = \frac{V_\alpha^2[p_S(1 - p_S) + p_E(1 - p_E)]}{(p_E - p_S)^2} \quad (19)$$

This procedure can be made logically consistent by basing the calculations on expression (15) instead of on (14), in which case the formula becomes

$$N = \frac{K_\alpha^2(p_S + p_E) \left(1 - \frac{p_S + p_E}{2}\right)}{(p_E - p_S)^2} \quad (20)$$

where K_α is the normal deviate exceeded with probability α , as given in Table 1.1 of Chap. 1.†

In general, (20) solves correctly the following problem: If the proportion of successes is p_S for the standard and p_E for the experimental method, how large must be the number of trials from which these proportions were computed before the experiment can be regarded as indicative of a real difference? The question stated is, however, of little or no practical significance. The practical problem exists only because it cannot be assumed that the proportions shown in the experiment are

* See Chap. 16 for an account of the inverse sine transformation for percentages.

† The value of K_α^2 can be found from tables of the chi-square distribution, for example, Table IV in Fisher and Yates, *Statistical Tables*, thus eliminating the need of squaring K_α . Since the probability that χ^2 will exceed a certain level is the probability that χ will exceed the square root of that level plus the probability that $-\chi$ will exceed the square root of that level, the probabilities given in the χ^2 tables must be halved for the present purposes.

the true proportions. If they were, we should be able to decide without difficulty which method is superior. Furthermore, even if we were willing to accept the proportions p_s and p_E shown in the experiment as suitable approximations of the true long-run proportions P_s and P_E , we could compute N from (20) only after carrying out the experiment to find p_s and p_E .

To determine a useful formula for N , we must think of formula (11) or its equivalent, formula (15), as constituting a rule according to which we decide from the data which of two actions to take. If the formula yields a value above some predetermined critical level, we accept the experimental method as superior, and if it yields a lower value we do not accept it (that is, for practical purposes we reject it). If the true proportion of successes for the experimental method is the same as the true proportion of successes for the standard method, it is important that the critical level of χ be such that there is only a small probability, say α , that the data will lead to a value of χ above the critical level. Similarly, if the true proportion of successes is P_s for the standard method but P_E ($P_E > P_s$) for the experimental method, it is important that the critical level of χ and the sample size N be such that there is only a small probability, say β , that the data will lead to a value of χ below the critical level.

The first condition, that the probability be only α of accepting the experimental method as superior when the true probabilities of success are equal, is met simply by selecting the critical level of χ as K_α , the normal deviate exceeded with probability α . Then, regardless of the sample size, the probability is α that the experimental method will be accepted when the true probabilities of success are the same for both methods.

On the other hand, for small samples the probability that χ will exceed K_α will not be much more than α even when the true probabilities are P_s and P_E . This probability of accepting the experimental method when the true probabilities are P_s and P_E will, however, increase as the sample size increases; and the problem is to find that value of N for which it is $1 - \beta$.

The required value of N , the size of the sample to be used with each method, is given by

$$N = \frac{1}{2} \left(\frac{K_\alpha + K_\beta}{\arcsin \sqrt{P_s} - \arcsin \sqrt{P_E}} \right)^2 \quad (21)$$

if angles are measured in radians, or by

$$N = 1641.6 \left(\frac{K_\alpha + K_\beta}{\arcsin \sqrt{P_s} - \arcsin \sqrt{P_E}} \right)^2 \quad (22)$$

if angles are measured in degrees, where K_ϵ is defined by

$$\frac{1}{\sqrt{2\pi}} \int_{K_\epsilon}^{\infty} e^{-\frac{x^2}{2}} dx = \epsilon \quad (23)$$

α is the probability of an error of the "first kind," that is, of accepting the experimental method as superior when actually the probability of success is the same for both methods

β is the probability of an error of the "second kind," that is, of rejecting the experimental method when the true probabilities for the standard and experimental methods are P_s and P_E , respectively.*

Values of N can be read directly from the nomogram of Fig. 7.1.

The choice of P_s can usually be based upon previous experience with the standard method, which will indicate approximately its proportion of successes. The value of P_E may then be chosen enough above P_s so that the difference is one that it is important to detect when present. Moderate variations in the values of P_s and P_E are not serious if P_s and P_E are affected alike. If the angular difference, the square of which constitutes the denominator of formula (22), is accepted as the appropriate measure of the difference between two percentages, it is not necessary to choose P_s and P_E individually but only to determine the angular difference that should be detected.†

To illustrate the application of formula (21), suppose $P_s = 0.010$, $P_E = 0.025$, $\alpha = 0.05$, and $\beta = 0.10$. From Table 1.1 of Chap. 1, we find $K_\alpha = 1.645$ and $K_\beta = 1.282$. From trigonometric tables,‡ we find $\arcsin 0.1000$ and $\arcsin 0.1581$ to be, respectively, 0.1002 and 0.1588 radians. Substituting these figures into (18), we have

$$N = \frac{(1.645 + 1.282)^2}{2(0.1588 - 0.1002)^2} \quad (24)$$

$$= 1,246$$

* If only one method is involved in an experiment, and if it is desired that the probability of approving it be α or $1 - \beta$ according as its true probability of success is P_s or P_E , formula (21) will indicate twice the appropriate sample size; that is, the appropriate sample size is given by substituting 4 for 2 in the denominator of formula (21). This was the method of computing the sample sizes N_α given in Table 1.3 of Chap. 1 for acceptance-inspection plans based on attributes. For that application, the first sentence of this footnote should be changed to read as follows: If only one product is involved in an inspection plan, and if it is desired that the probability of rejecting be α or $1 - \beta$ according as the true probability of a defective is p_1 or p_2 , formula (21) will indicate twice the appropriate sample size.

† In this connection, see Statistical Research Group, *Sequential Analysis*, Sec. 3.62, pp. 3.47-3.50, especially Table 3.61 and Fig. 3.61; also Secs. 3.21 and 3.22, pp. 3.09-3.10.

‡ For example, Mathematical Tables Project, *Arc sin x*.

If the nomogram is used, we pass a line between 0.05 on the α scale and 0.10 on the β scale and mark its point of intersection with the A scale. Another line is passed between 0.01 on the P_s scale and 0.025 on the P_E scale, and the point of intersection of this line with the B scale is marked. The N scale is calibrated so that the number of trials needed for each method can be read off where the N scale is intersected by a straight line between the points marked on the A and B scales. In this example, the point of intersection falls about halfway between $N = 1,200$ and $N = 1,300$.

4. OPERATING CHARACTERISTICS

Conclusions drawn from double dichotomies depend upon two quantities, one characterizing the amount of data collected and the other characterizing the method of analyzing the data. These quantities are N , the number of observations with each method, and K_α , the critical level of χ which, if equaled or exceeded, leads to acceptance of the experimental method as superior. Formula (21) can be used to determine the operating characteristics of any plan for analyzing a double dichotomy defined by given values of N and K_α .

By the operating characteristics of a plan is meant the probability, as a function of the true nature of the populations, that the plan will lead to accepting the experimental method as superior. In this case, the operating characteristics may be represented by a surface rather than a curve, for the true nature of the populations is measured by two parameters P_s and P_E . If in the plane of the page we measure P_E lengthwise and P_s crosswise, any point for which P_E and P_s are both between 0 and 1 represents a possible combination of P_E and P_s . Vertically above each point we may erect a line whose height represents the probability that a test using the given N and K_α will lead to accepting the experimental method as superior. The surface formed by the tops of these lines is the OC surface. A test is satisfactory if its OC surface shows high probabilities of accepting the experimental method when its superiority is sufficient to make such acceptance important, and low probabilities of accepting the experimental when its superiority is so small (especially when it is zero or negative) as to make its acceptance undesirable.

We may rewrite (21) as

$$-K_\beta = K_\alpha - \sqrt{2N} (\arcsin \sqrt{P_E} - \arcsin \sqrt{P_s}) \quad (25)$$

Formula (25) yields $-K_\beta$; the probability of accepting the experimental method is $1 - \beta$, which is the probability that a normal deviate will exceed $-K_\beta$ and may be obtained from Table 1.5 of Chap. 1. Thus, for any combination of P_E and P_s , formula (25) yields the probability that a test based on N and K_α will lead to acceptance of the experimental method.

Formula (25) does not depend upon the individual probabilities P_E and P_S but only upon their angular difference

$$T = \arcsin \sqrt{P_E} - \arcsin \sqrt{P_S} \quad (26)$$

so we may write it

$$K_\beta = \sqrt{2N} T - K_\alpha \quad (27)$$

Letting L_T denote the probability that a test defined by N and K_α will lead to acceptance of the experimental method when the true angular difference is T , and noting that $K_{1-\beta} = -K_\beta$, we have

$$L_T = \frac{1}{\sqrt{2\pi}} \int_{K_\alpha - \sqrt{2N} T}^{\infty} e^{-\frac{x^2}{2}} dx \quad (28)$$

as the equation of the OC curve in terms of T . Values of L_T can be obtained from Table 1.5, Chap. 1, by taking

$$K_\epsilon = K_\alpha - \sqrt{2N} T \quad (29)$$

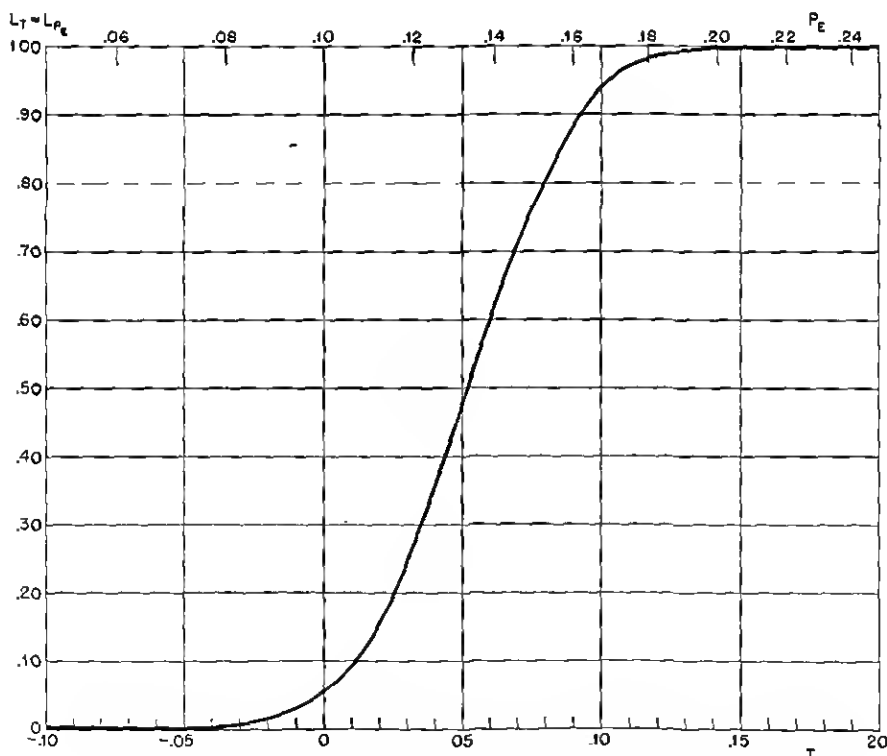


FIG. 7.2.—Operating-characteristic curve for a comparison of two percentages, $N = 500$, $K_\alpha = 1.645$.

Figure 7.1 can be used to determine L_T from (28). The given values of P_E and P_S determine a point on the B scale. A line is drawn through the point on the B scale and the given value of N on the N scale and extended until it intersects the A scale. This point on the A scale and the given value of α on the α scale determine a line whose intersection with the β scale gives $1 - L_T$.

In evaluating a proposed test, it is sometimes helpful to plot the OC curve against the true proportion of successes for the experimental method, assuming some value, say P'_S , for the proportion of successes with the standard method. This gives a picture, the significance of which depends on the validity of the value used for P'_S , of the absolute level of performance by the experimental method that will result in a high probability of its acceptance or rejection. Such a picture can be obtained from formula (25), replacing P_S by P'_S and calculating $L_T = 1 - \beta$ for various values of P_E .

Figure 7.2 shows the OC curve for an analysis based on a sample size N of 500 for each method and a critical level of χ , K_α , of 1.645. Two horizontal scales are shown, the lower in terms of T , the true angular difference between the two probabilities, and the upper in terms of P_E on the assumption that $P_S = 0.10$.

5. TECHNICAL NOTES

Let s_E and s_S be the observed numbers of successes in N trials with the experimental and standard methods, respectively. Then the observed proportions of successes with the two methods are

$$p_E = \frac{s_E}{N} \quad \text{and} \quad p_S = \frac{s_S}{N} \quad (30)$$

When we are interested only in alternative hypotheses for which P_E , the true proportion of successes with the experimental method, is greater than P_S , the long-run proportion of successes with the standard method, the classical test with level of significance α is to reject the null hypothesis that $P_E = P_S$ if

$$\frac{\sqrt{N}(p_E - p_S)}{\sqrt{(p_E + p_S)\left(1 - \frac{p_E + p_S}{2}\right)}} \geq K_\alpha \quad (31)$$

where

$$\frac{1}{\sqrt{2\pi}} \int_{K_\alpha}^{\infty} e^{-\frac{x^2}{2}} dx = \alpha \quad (32)$$

Except when N is very small, or P_E or P_S very close to 0 or 1, this test is essentially equivalent to the criterion: Reject the null hypothesis if*

$$\sqrt{2N} (\arcsin \sqrt{p_E} - \arcsin \sqrt{p_S}) \geq K_\alpha \quad (33)$$

* See Chap. 16 for a discussion of the inverse sine transformation of percentages, upon which what follows is based.

CHAPTER 8

PLANNING AND INTERPRETING EXPERIMENTS FOR COMPARING TWO STANDARD DEVIATIONS

	PAGE
1. Introduction.	269
2. Experiments to Determine Whether a New Product Is More Variable Than a Standard Product.	269
2.1 Problem.	269
2.2 General Procedure for Basing an Answer on Observational Data.	270
2.3 Standard Procedure.	270
2.4 Operating Characteristics of the Standard Procedure	271
3. Experiments to Determine Whether a New Product Is Less Variable Than a Standard Product.	278
3.1 Problem.	278
3.2 Illustration.	280
4. Experiments to Determine Whether a Particular One of Two New Products Is More Variable Than the Other.	280
4.1 Problem.	280
4.2 Standard Procedure When Product 1 Is to Be Chosen Unless σ_1^2 Is Larger Than σ_2^2	281
4.2.1 Procedure.	281
4.2.2 Two Special Cases.	282
4.2.3 Illustrations.	282
4.3 Procedure When It Is Immaterial Which Product Is Chosen If $\sigma_1^2 = \sigma_2^2$	283
5. Experiments Involving the Analysis of Variance	297
5.1 Systematic and Random Variation	297
5.2 A Typical Analysis of Variance.	311
5.3 Illustrations	313
6. Technical Notes	314
6.1 Method of Construction and Accuracy of Tables 8.1 and 8.2	314
6.2 Method of Construction and Accuracy of Tables 8.3 and 8.4	316
7. References.	318

FIGURES

8.1 Operating-characteristic Curves for Experiments to Determine Whether a New Product (Process) Is More Variable Than a Standard Product (Process) of Known Variability, 0.05 Level of Significance.	274
8.2 Operating-characteristic Curves for Experiments to Determine Whether a New Product (Process) Is More Variable Than a Standard Product (Process) of Known Variability, 0.01 Level of Significance.	275
8.3 Operating-characteristic Curves for Experiments to Determine Whether a Particular One of Two New Products (Processes) Is More Variable Than the Other, 0.05 Level of Significance.	296
8.4 Operating-characteristic Curves for Experiments to Determine Whether a Particular One of Two New Products (Processes) Is More Variable Than the Other, 0.01 Level of Significance.	297

TABLES

8.1 Values of $\rho(0.05, \beta, n_1)$ Corresponding to Selected Values of β and n_1	272
8.2 Values of $\rho(0.01, \beta, n_1)$ Corresponding to Selected Values of β and n_1	276
8.3 Values of $\phi(0.05, \beta, n_1, n_2)$ Corresponding to Selected Values of β , n_1 , and n_2	284
8.4 Values of $\phi(0.01, \beta, n_1, n_2)$ Corresponding to Selected Values of β , n_1 , and n_2	298

This chapter was prepared by
Churchill Eisenhart, National Bureau of Standards

CHAPTER 8

PLANNING AND INTERPRETING EXPERIMENTS FOR COMPARING TWO STANDARD DEVIATIONS

1. INTRODUCTION

The present chapter is concerned with the planning and interpretation of experiments to determine whether (1) a given product, or process, is more (or less) variable than a standard product, or process; (2) one of two new products, or processes, is more (or less) variable than the other; (3) the random variation of a product, or process, has a component assignable to a specific source of variation.

With regard to proposed experiments, the problem considered is that of determining how many observations will be required in order to render the discriminating power of the experiment adequate for the purposes at hand. The solutions to this problem, in addition to being useful in the planning of experiments, provide a means of evaluating the discriminating power of an experiment already carried out. Thus, in planning experiments for the three purposes listed above, the results given below will enable a research worker to formulate an experiment the size of which, on the one hand, is compatible with the cost (monetary expense, time, inconvenience, and so forth) of obtaining the observations and, on the other, limits to a known extent the risks of making erroneous decisions of practical significance. Alternatively, in the case of experiments already conducted, the results given below will enable the experimenter to judge the confidence that he can place in conclusions based on the data obtained.

2. EXPERIMENTS TO DETERMINE WHETHER A NEW PRODUCT IS MORE VARIABLE THAN A STANDARD PRODUCT

2.1. Problem

The following situation is common in practical work: A certain product has been in use for some time and its variability with respect to some important measurable characteristic x is known. Let σ_0^2 denote the known variance (squared standard deviation) of x for this standard product. A new product is under consideration, whose variability with respect to x is unknown; let σ_1^2 denote the unknown variance of x for the new product. Since the value of σ_1^2 is unknown, it is not possible to

decide with certainty whether the variability of the new product is more than that of the standard, that is, whether $\sigma_1^2/\sigma_0^2 > 1$.

2.2. General Procedure for Basing an Answer on Observational Data

An answer to this question can, however, be obtained by computing an estimate s_1^2 of σ_1^2 from values of x observed in a sample of the new product and agreeing that $s_1^2/\sigma_0^2 > C$ will be taken to imply that $\sigma_1^2/\sigma_0^2 > 1$, and $s_1^2/\sigma_0^2 \leq C$ will be taken to imply that $\sigma_1^2/\sigma_0^2 \leq 1$, where C is some positive constant chosen in advance, that is, before the value of s_1^2 has been obtained, preferably before the experiment determining the value of s_1^2 is carried out. It is evident that if C is very large, application of this procedure will almost always lead to the decision that the new product is not more variable than the standard ($\sigma_1^2 \leq \sigma_0^2$); if C is very small, the decision will almost always be that the new is more variable than the standard ($\sigma_1^2 > \sigma_0^2$). Clearly, some intermediate value of C is called for—a value that will not lead too frequently to the decision $\sigma_1^2/\sigma_0^2 > 1$ when the reverse is true and yet will lead to this decision in most of the cases in which the excess of σ_1^2 over σ_0^2 is of practical importance.

2.3. Standard Procedure*

The standard procedure is to use as an estimate of σ_1^2 a function s_1^2 of the observed values of x that has the property that in repeated sampling $n_1 s_1^2/\sigma_1^2$ is distributed, at least to a good approximation, as χ^2 for n degrees of freedom, and to

a. Conclude $\sigma_1^2/\sigma_0^2 \leq 1$ whenever†

$$\frac{s_1^2}{\sigma_0^2} \leq \frac{\chi_\alpha^2(n_1)}{n_1} \quad (1)$$

b. Conclude $\sigma_1^2/\sigma_0^2 > 1$ whenever

$$\frac{s_1^2}{\sigma_0^2} > \frac{\chi_\alpha^2(n_1)}{n_1} \quad (2)$$

where $\chi_\alpha^2(n_1)$ is the α level of significance of χ^2 for n_1 degrees of freedom, that is

$$\alpha = P\{\chi^2(n_1) > \chi_\alpha^2(n_1)\} = \frac{1}{\Gamma\left(\frac{n_1}{2}\right)} \int_{\chi_\alpha^2(n_1)}^{\infty} \left(\frac{1}{2} \chi^2\right)^{\frac{1}{2}(n_1-2)} e^{-\frac{1}{2}\chi^2} d\left(\frac{1}{2} \chi^2\right) \quad (3)$$

for $n = n_1$.†

* See FISHER, *Statistical Methods*, Chap. IV, Sec. 21.03. (For full citations, see Sec. 7).

† See Sec. 6, below, for a discussion of published tables of this integral.

Example I. The variance σ_0^2 of a particular dimension of a standard product is 3.2 cm.² From measurements of the dimension on 10 items of a new product it is found that $s_1^2 = 4.8$, with 9 degrees of freedom. Does the variance σ_1^2 of the dimension with the new product exceed the variance σ_0^2 of the dimension with the standard product?

If we conduct the test at the 0.05 level of significance, we find $s_1^2/\sigma_0^2 = 1.5 < 1.880 = \chi_{0.05}^2(9)/9$ and are led to conclude $\sigma_1^2/\sigma_0^2 \leq 1$; that is, we conclude that the variability of the new product does not exceed the standard in respect of the dimension in question.

2.4. Operating Characteristics of the Standard Procedure

The question arises, what are the chances of the standard rule leading to a wrong conclusion? That is, when in fact $\sigma_1^2/\sigma_0^2 \leq 1$, how often will it lead to the conclusion $\sigma_1^2/\sigma_0^2 > 1$, termed an error of the first kind;* and when in fact $\sigma_1^2/\sigma_0^2 > 1$, how often will it lead to the conclusion $\sigma_1^2/\sigma_0^2 \leq 1$, termed an error of the second kind? In other words, what are the operating characteristics of the procedure?

Clearly, the chance of an erroneous decision will depend on σ_0^2 , n_1 , and α , as these quantities are involved explicitly in inequalities (1) and (2). Intuition tells us that the chance of error depends also on the actual value of σ_1^2/σ_0^2 , that is, upon

$$\rho = \frac{\sigma_1^2}{\sigma_0^2} \quad (4)$$

To begin with, it is clear from (3) that the probability of an error of the first kind is exactly α when $\rho = 1$. Second, it will be shown in Sec. 6 that the probability of an error of the second kind will be exactly β if ρ has the value

$$\rho(\alpha, \beta, n_1) = \frac{\chi_{\alpha}^2(n_1)}{\chi_{1-\beta}^2(n_1)} \quad (5)$$

This equation has been used to compute tables of $\rho(\alpha, \beta, n_1)$ corresponding to $\alpha = 0.05$ and 0.01 and to a wide selection of values of β and n_1 . These are published as Tables 8.1 and 8.2, pp. 272-273 and 276-277; the method of their construction and the accuracy of interpolation is discussed in Sec. 6.

The following examples illustrate the use of Tables 8.1 and 8.2 in the interpretation of the results of experiments already carried out and in the planning of experiments:

Example II. For what value of the ratio σ_1^2/σ_0^2 is the probability of an error of the second kind equal to 0.50 when the test of Example I is employed?

* This terminology was introduced by Neyman and Pearson.

TABLE 8.1
VALUES OF $\rho(0.05, \beta, n_1)$ CORRESPONDING TO SELECTED VALUES OF β AND n_1

De- grees of freedom	β	0.005													
		0.01	0.025	0.05	0.10	0.25	0.50	0.75	0.90	0.95	0.975	0.99	0.995		
1	97821.	24454.	3911.6	976.94	243.27	37.835	8.4439	2.9029	1.4198	1.0000	0.7646	0.5790	0.4875		
2	597.65	298.07	118.33	58.404	28.433	10.413	4.3219	2.1610	1.3010	1.0000	0.8121	0.6505	0.5654		
3	108.96	68.054	36.214	22.211	13.373	6.4450	3.3030	1.9022	1.2501	1.0000	0.8359	0.6888	0.6087		
4	45.837	31.933	19.586	13.349	8.9202	4.9350	2.8265	1.7618	1.2196	1.0000	0.8514	0.7146	0.6385		
5	26.887	19.972	13.318	9.6045	6.8748	4.1391	2.5441	1.6708	1.1986	1.0000	0.8627	0.7338	0.6609		
6	18.634	14.438	10.176	7.6904	5.7127	3.6449	2.3544	1.6059	1.1829	1.0000	0.8714	0.7490	0.6789		
7	14.220	11.353	8.3244	6.4905	4.9653	3.3061	2.2168	1.5566	1.1706	1.0000	0.8785	0.7614	0.6937		
8	11.535	9.4184	7.1143	5.6748	4.4439	3.0583	2.1115	1.5175	1.1606	1.0000	0.8844	0.7719	0.7063		
9	9.7520	8.1033	6.2654	5.0883	4.0591	2.8682	2.0280	1.4856	1.1522	1.0000	0.8894	0.7809	0.7172		
10	8.4918	7.1562	5.6382	4.6461	3.7629	2.7173	1.9397	1.4589	1.1451	1.0000	0.8938	0.7888	0.7268		
11	7.5580	6.4435	5.1563	4.3007	3.5274	2.5942	1.9026	1.4361	1.1389	1.0000	0.8976	0.7958	0.7353		
12	6.8404	5.8887	4.7745	4.0233	3.3355	2.4917	1.8541	1.4163	1.1335	1.0000	0.9010	0.8020	0.7430		
13	6.2726	5.4450	4.4646	3.7954	3.1758	2.4048	1.8122	1.3990	1.1287	1.0000	0.9040	0.8076	0.7499		
14	5.8127	5.0821	4.2078	3.6046	3.0406	2.3300	1.7756	1.3837	1.1244	1.0000	0.9068	0.8128	0.7562		
15	5.4328	4.7799	3.9916	3.4425	2.9246	2.2648	1.7432	1.3700	1.1205	1.0000	0.9093	0.8174	0.7620		
16	5.1138	4.5243	3.8068	3.3029	2.8238	2.2075	1.7144	1.3577	1.1170	1.0000	0.9116	0.8218	0.7674		
17	4.8422	4.3053	3.6471	3.1813	2.7354	2.1566	1.6885	1.3465	1.1138	1.0000	0.9138	0.8257	0.7723		
18	4.6082	4.1154	3.5075	3.0743	2.6571	2.1111	1.6651	1.3362	1.1108	1.0000	0.9157	0.8295	0.7770		
19	4.4044	3.9492	3.3844	2.9795	2.5872	2.0700	1.6438	1.3269	1.1081	1.0000	0.9175	0.8329	0.7813		
20	4.2253	3.8025	3.2750	2.8948	2.5244	2.0328	1.6243	1.3182	1.1055	1.0000	0.9192	0.8361	0.7853		
21	4.0667	3.6720	3.1772	2.8185	2.4676	1.9989	1.6064	1.3102	1.1032	1.0000	0.9208	0.8392	0.7891		
22	3.9252	3.5551	3.0890	2.7496	2.4160	1.9678	1.5899	1.3028	1.1010	1.0000	0.9223	0.8420	0.7927		
23	3.7982	3.4497	3.0092	2.6869	2.3689	1.9392	1.5746	1.2959	1.0989	1.0000	0.9238	0.8447	0.7961		

TABLE 8.1

COMPARING TWO STANDARD DEVIATIONS

273

TABLE 8.1.—(Continued)

De- grees of freedom	β	0.005	0.01	0.025	0.05	0.10	0.25	0.50	0.75	0.90	0.95	0.975	0.99	0.995
24		3.6834	3.3543	2.9364	2.6296	2.3256	1.9128	1.5604	1.2894	1.0970	1.0000	0.9251	0.8473	0.7993
25		3.5792	3.2673	2.8699	2.5709	2.2877	1.8894	1.5472	1.2834	1.0951	1.0000	0.9263	0.8497	0.8023
26		3.4842	3.1873	2.8088	2.5284	2.2488	1.8556	1.5348	1.2777	1.0934	1.0000	0.9275	0.8520	0.8052
27		3.3972	3.1147	2.7525	2.4836	2.2145	1.8443	1.5231	1.2723	1.0918	1.0000	0.9287	0.8541	0.8080
28		3.3172	3.0474	2.7004	2.4420	2.1826	1.8245	1.5122	1.2672	1.0902	1.0000	0.9297	0.8562	0.8106
29		3.2434	2.9851	2.6520	2.4032	2.1529	1.8058	1.5019	1.2624	1.0888	1.0000	0.9308	0.8582	0.8132
30		3.1750	2.9273	2.6070	2.3670	2.1250	1.7883	1.4921	1.2578	1.0874	1.0000	0.9318	0.8601	0.8156
40		2.6928	2.5157	2.2821	2.1034	1.9194	1.6365	1.4175	1.2223	1.0763	1.0000	0.9396	0.8755	0.8351
50		2.4117	2.2724	2.0862	1.9418	1.7911	1.5720	1.3683	1.1983	1.0687	1.0000	0.9452	0.8864	0.8492
60		2.2255	2.1097	1.9535	1.8311	1.7022	1.5123	1.3328	1.1807	1.0630	1.0000	0.9494	0.8948	0.8600
70		2.0920	1.9922	1.8568	1.7498	1.6362	1.4673	1.3057	1.1670	1.0585	1.0000	0.9527	0.9015	0.8687
80		1.9909	1.9029	1.7826	1.6870	1.5850	1.4320	1.2842	1.1560	1.0549	1.0000	0.9555	0.9070	0.8758
90		1.9114	1.8322	1.7235	1.6368	1.5438	1.4034	1.2665	1.1469	1.0519	1.0000	0.9578	0.9116	0.8819
100		1.8468	1.7747	1.6753	1.5956	1.5098	1.3795	1.2518	1.1393	1.0493	1.0000	0.9597	0.9156	0.8871
120		1.7479	1.6861	1.6005	1.5315	1.4566	1.3420	1.2282	1.1270	1.0452	1.0000	0.9629	0.9221	0.8957
∞		1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

Explanation

Let (a) s_1^2 be an estimate of σ_1^2 such that $\frac{n_1 s_1^2}{\sigma_1^2}$ is distributed as χ^2 for n_1 degrees of freedom

(b) $\chi_{n_1}^2(n_1)$ be the value of χ^2 for n_1 degrees of freedom exceeded with probability ϵ

(c) the decision $\frac{\sigma_1^2}{\sigma_0^2} > 1$, or the decision $\frac{\sigma_1^2}{\sigma_0^2} \leq 1$, be made according as $\frac{s_1^2}{\sigma_0^2}$ exceeds or does not exceed $\frac{1}{n_1} \chi_{n_1, \epsilon}^2(n_1)$

Then the probability is β that the decision $\frac{\sigma_1^2}{\sigma_0^2} \leq 1$ will be made when $\frac{\sigma_1^2}{\sigma_0^2} = \rho(0.05, \beta, n_1) = \frac{\chi_{n_1, \epsilon}^2(n_1)}{\chi_{n_1, \beta}^2(n_1)}$

For $\alpha = 0.05$, $n_1 = 9$, and $\beta = 0.50$, we find from Table 8.1 that $\rho(0.05, 0.50, 9) = 2.0280$. This means that if σ_1^2 is roughly double σ_0^2 (that is, if the standard deviation of the new product is roughly 1.4 times that of the standard) and the test is conducted at the 0.05 level of significance, with s_1^2 based on only 9 degrees of

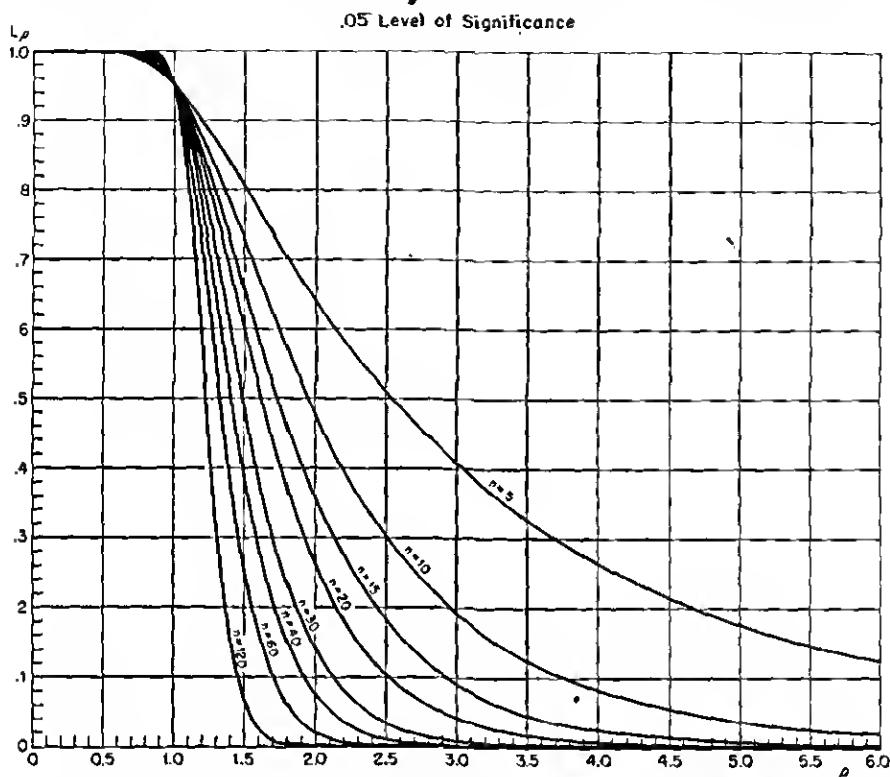


FIG. 8.1.—Operating-characteristic curves for experiments to determine whether a new product (process) is more variable than a standard product (process) of known variability, 0.05 level of significance.

freedom, then there is approximately an even chance that the test will lead to the wrong conclusion, $\sigma_1^2/\sigma_0^2 \leq 1$. If, to ensure a smaller risk of committing an error of the first kind, the test is conducted at the 0.01 level of significance, the situation is worse, for

$$\rho(0.01, 0.50, 9) = 2.5970$$

(from Table 8.2). Clearly 9 degrees of freedom for s_1^2 are too few if a decision that $\sigma_1^2/\sigma_0^2 \leq 1$ is a serious error from the practical viewpoint when σ_1^2 is double σ_0^2 .

Example III. If a decision that $\sigma_1^2/\sigma_0^2 \leq 1$ is a serious error from the practical viewpoint when $\sigma_1 = 1.5\sigma_0$ ($\rho = 2.25$), and it is

desired to keep the risk of such an error below 0.05 ($\beta = 0.05$) when the test is conducted at the 0.05 level of significance ($\alpha = 0.05$), how many degrees of freedom will be needed for s_1^2 ?

On looking in the $\beta = 0.05$ column of Table 8.1, we find that $n_1 = 30$ is not quite sufficient, since $\rho(0.05, 0.05, 30) = 2.3670$; but

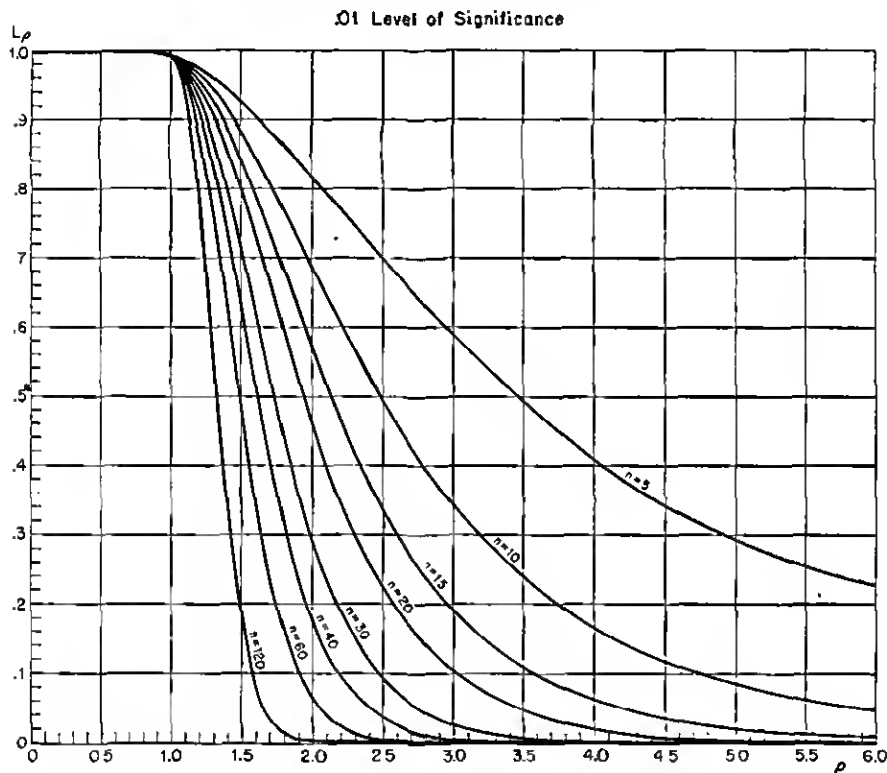


FIG. 8.2.—Operating-characteristic curves for experiments to determine whether a new product (process) is more variable than a standard product (process) of known variability, 0.01 level of significance.

$n_1 = 40$ is ample, since $\rho(0.05, 0.05, 40) = 2.1034$. By interpolation, using $1/\sqrt{n_1}$ as argument, it is found that 34 (33.7) degrees of freedom are needed (linear interpolation gives 34.4, which would be taken as 35).

If $\sigma_0 = 1.79$ cm. ($\sigma_0^2 = 3.2$ cm.²) as in Example I, so that $\sigma_1 = 1.5\sigma_0 = 2.69$ cm., and it is felt that this is too large an excess to have undetected 1 time in 20, but failure to detect that $\sigma_1 > \sigma_0$ when $\sigma_1 = 2.00$ cm., say, could be tolerated 1 time in 20, then $\rho = 1.25$, and it is clear from an examination of Table 8.1 that a very large number of degrees of freedom, over 400, are needed—

TABLE 8.2

VALUES OF $\rho(0.01, \beta, n_1)$ CORRESPONDING TO SELECTED VALUES OF β AND n_1

β	0.005	0.01	0.025	0.05	0.10	0.25	0.50	0.75	0.90	0.95	0.975	0.99	0.995
1	168950.	42237.	6756.0	1687.4	420.19	65.349	14.584	5.0139	2.4523	1.7272	1.3207	1.0000	0.8421
2	918.73	458.21	181.89	89.781	43.709	16.008	6.6439	3.3219	2.0000	1.5372	1.2484	1.0000	0.8692
3	158.18	98.796	52.573	32.244	19.414	9.3564	4.7950	2.7614	1.8148	1.4517	1.2136	1.0000	0.8837
4	64.142	44.686	27.408	18.081	12.482	6.9058	3.9553	2.4634	1.7066	1.3994	1.1915	1.0000	0.8934
5	36.640	27.217	18.150	13.170	9.3686	5.4406	3.4670	2.2769	1.6334	1.3627	1.1756	1.0000	0.9007
6	24.880	19.278	13.587	10.280	7.6275	4.8605	3.1435	2.1442	1.5794	1.3352	1.1635	1.0000	0.9064
7	18.676	14.911	10.933	8.5244	6.5212	4.3422	2.9114	2.0441	1.5374	1.3134	1.1538	1.0000	0.9111
8	14.943	12.202	9.2168	7.3519	5.7573	3.9621	2.7353	1.9660	1.5036	1.2955	1.1457	1.0000	0.9151
9	12.488	10.377	8.0233	6.5159	5.1680	3.6725	2.5970	1.9024	1.4755	1.2806	1.1389	1.0000	0.9185
10	10.766	9.0725	7.1480	5.8902	4.7705	3.4449	2.4845	1.8495	1.4518	1.2678	1.1331	1.0000	0.9214
11	9.4979	8.0973	6.4797	5.4046	4.4328	3.2601	2.3910	1.8047	1.4313	1.2567	1.1280	1.0000	0.9241
12	8.5291	7.3425	5.9533	5.0166	4.1589	3.1069	2.3118	1.7660	1.4134	1.2469	1.1234	1.0000	0.9264
13	7.7666	6.7419	5.5280	4.6994	3.9322	2.9775	2.2438	1.7323	1.3976	1.2382	1.1194	1.0000	0.9285
14	7.1518	6.2529	5.1773	4.4351	3.7411	2.8607	2.1846	1.7025	1.3835	1.2304	1.1157	1.0000	0.9305
15	6.6460	5.8474	4.8830	4.2113	3.5777	2.7706	2.1325	1.6760	1.3708	1.2233	1.1124	1.0000	0.9322
16	6.2229	5.5056	4.6325	4.0193	3.4363	2.6863	2.0862	1.6521	1.3593	1.2169	1.1094	1.0000	0.9338
17	5.8640	5.2138	4.4167	3.8526	3.3126	2.6117	2.0448	1.6306	1.3488	1.2110	1.1066	1.0000	0.9353
18	5.5557	4.9616	4.2287	3.7065	3.2035	2.5451	2.0075	1.6110	1.3392	1.2056	1.1040	1.0000	0.9367
19	5.2880	4.7415	4.0634	3.5772	3.1063	2.4853	1.9736	1.5931	1.3304	1.2006	1.1016	1.0000	0.9380
20	5.0534	4.5477	3.9169	3.4621	3.0192	2.4312	1.9427	1.5766	1.3222	1.1960	1.0994	1.0000	0.9392
21	4.8461	4.3758	3.7861	3.3587	2.9406	2.3820	1.9143	1.5614	1.3146	1.1917	1.0973	1.0000	0.9404
22	4.6617	4.2221	3.6686	3.2655	2.8693	2.3370	1.8882	1.5473	1.3075	1.1876	1.0954	1.0000	0.9414
23	4.4964	4.0839	3.5623	3.1808	2.8043	2.2957	1.8641	1.5341	1.3009	1.1838	1.0936	1.0000	0.9424
24	4.3474	3.9589	3.4658	3.1036	2.7448	2.2577	1.8417	1.5219	1.2947	1.1803	1.0919	1.0000	0.9434

TABLE 8.2

COMPARING TWO STANDARD DEVIATIONS

277

TABLE 8.2.—(Continued)

Do- grees of freedom	β	0.005	0.01	0.025	0.05	0.10	0.25	0.50	0.75	0.90	0.95	0.975	0.99	0.995
25		4.2125	3.8454	3.3777	3.0328	2.6900	2.2225	1.8209	1.5104	1.2889	1.1769	1.0902	1.0000	0.9443
26		4.0896	3.7417	3.2969	2.9678	2.6393	2.1897	1.8014	1.4997	1.2834	1.1738	1.0887	1.0000	0.9452
27		3.9774	3.6466	3.2225	2.9077	2.5927	2.1593	1.7832	1.4895	1.2782	1.1708	1.0872	1.0000	0.9460
28		3.8743	3.5591	3.1538	2.8520	2.5491	2.1308	1.7661	1.4800	1.2733	1.1679	1.0859	1.0000	0.9468
29		3.7792	3.4783	3.0901	2.8003	2.5085	2.1042	1.7500	1.4710	1.2686	1.1652	1.0845	1.0000	0.9475
30		3.6914	3.4034	3.0310	2.7520	2.4706	2.0791	1.7348	1.4624	1.2642	1.1626	1.0833	1.0000	0.9482
40		3.0759	2.8736	2.6067	2.4026	2.1924	1.8922	1.6192	1.3062	1.2294	1.1423	1.0733	1.0000	0.9539
50		2.7207	2.5635	2.3535	2.1906	2.0206	1.7734	1.5436	1.3518	1.2056	1.1281	1.0663	1.0000	0.9580
60		2.4871	2.3577	2.1832	2.0464	1.9023	1.6901	1.4895	1.3195	1.1879	1.1176	1.0610	1.0000	0.9612
70		2.3206	2.2100	2.0507	1.9410	1.8151	1.6277	1.4484	1.2945	1.1742	1.1093	1.0568	1.0000	0.9636
80		2.1951	2.0980	1.9634	1.8600	1.7476	1.5789	1.4150	1.2746	1.1631	1.1026	1.0535	1.0000	0.9657
90		2.0967	2.0098	1.8907	1.7955	1.6935	1.5394	1.3893	1.2581	1.1539	1.0970	1.0506	1.0000	0.9674
100		2.0171	1.9383	1.8297	1.7427	1.6490	1.5067	1.3672	1.2443	1.1461	1.0922	1.0482	1.0000	0.9689
120		1.8956	1.8286	1.7358	1.6609	1.5797	1.4553	1.3320	1.2222	1.1335	1.0845	1.0443	1.0000	0.9713
∞		1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

Explanation

Let (a) s_1^2 be an estimate of σ_1^2 such that $\frac{n_1 s_1^2}{\sigma_1^2}$ is distributed as χ^2 for n_1 degrees of freedom

(b) $\chi_{\alpha}^2(n_1)$ be the value of χ^2 for n_1 degrees of freedom exceeded with probability α

(c) the decision $\frac{\sigma_1^2}{\sigma_0^2} > 1$, or the decision $\frac{\sigma_1^2}{\sigma_0^2} \leq 1$, be made according as $\frac{s_1^2}{\sigma_0^2}$ exceeds or does not exceed $\frac{\chi_{\alpha, n_1}^2}{n_1}$

Then the probability is β that the decision $\frac{\sigma_1^2}{\sigma_0^2} \leq 1$ will be made when $\frac{\sigma_1^2}{\sigma_0^2} = \rho(0.01, \beta, n_1) = \frac{\chi_{\beta, n_1}^2(n_1)}{\chi_{1-\beta, n_1}^2(n_1)}$.

an astonishingly large number to persons who have never investigated this matter before.*

As is pointed out in the footnote to the tables, $\rho(\alpha, \beta, n_1)$ is the value of σ_1^2/σ_0^2 for which the probability of the decision $\sigma_1^2/\sigma_0^2 \leq 1$ equals β when the test is conducted at the α level of significance with n_1 degrees of freedom. When $\rho(\alpha, \beta, n_1) \leq 1$, β can no longer be interpreted as the probability of an error of the second kind, since the decision $\sigma_1^2/\sigma_0^2 \leq 1$ is correct under these circumstances.† The values of $\rho(\alpha, \beta, n_1) < 1$ have been included in the tables since they are useful for drawing the operating-characteristic curves.

Let $L_\rho = L(\alpha, n_1, \rho)$ denote the probability that the decision $\sigma_1^2/\sigma_0^2 \leq 1$ will be made when $\sigma_1^2/\sigma_0^2 = \rho$ and the test defined by formulas (1) and (2) is conducted at the α level of significance with n_1 degrees of freedom for s_1^2 . Then L_ρ plotted as a function of ρ , for fixed values of α and n_1 , is termed the operating-characteristic curve of the test so defined. Since the probability that the decision $\sigma_1^2/\sigma_0^2 > 1$ will be reached is $1 - L_\rho$, in view of the exhaustive character of inequalities (1) and (2), it is clear that the curve L_ρ completely specifies the operating characteristics of the test, that is, the expected performance of the test in repeated applications. Thus, it is not necessary to plot the complementary curve $1 - L_\rho$, except perhaps for psychological reasons. A probability of 0.90 that a correct decision will be made may evoke less concern about the stringency of the test than a statement that the probability of an incorrect decision is 0.10.

Figure 8.1 shows the operating-characteristic curves corresponding to 5, 10, 15, 20, 30, 40, 60, and 120 degrees of freedom when $\alpha = 0.05$; Fig. 8.2 shows the corresponding curves when $\alpha = 0.01$.

3. EXPERIMENTS TO DETERMINE WHETHER A NEW PRODUCT IS LESS VARIABLE THAN A STANDARD PRODUCT

3.1. Problem

There are not many situations in which a new product is preferred to a standard product only if its variability exceeds that of the standard. Consequently, a test of the hypothesis $\sigma_1^2/\sigma_0^2 \geq 1$ relative to the alterna-

* The following formula may be used when n is large, say more than 30:

$$\begin{aligned} n &= \frac{1}{2} \left(\frac{K_\alpha \sigma_0 + K_\beta \sigma_1}{\sigma_1 - \sigma_0} \right)^2 \\ &= \frac{1}{2} \left(\frac{K_\alpha + K_\beta \sqrt{\rho}}{\sqrt{\rho} - 1} \right)^2 \end{aligned}$$

where K_ϵ denotes a normal deviate exceeded with probability ϵ and may be found from Table 1.1 of Chap. 1.

† From (5) it is clear that $\rho(\alpha, \beta, n_1) = 1$ for $\beta = 1 - \alpha$, and is less than 1 for $\beta > 1 - \alpha$, since χ^2_α increases as ϵ decreases, whatever the value of n .

tive $\sigma_1^2/\sigma_0^2 < 1$ is rarely employed. Nevertheless, there are situations in which too small a variability is disadvantageous. For instance, an average gunner is more likely to bring down a bird with a shotgun than with a rifle. It would not be advisable to reduce the dispersion of the shot to nearly zero.

In such cases the standard procedure is modified to

(a) Conclude $\sigma_1^2/\sigma_0^2 \geq 1$ whenever

$$\frac{s_1^2}{\sigma_0^2} \geq \frac{\chi_{1-\alpha}^2(n_1)}{n_1} \quad (6)$$

(b) Conclude $\sigma_1^2/\sigma_0^2 < 1$ whenever

$$\frac{s_1^2}{\sigma_0^2} < \frac{\chi_{1-\alpha}^2(n_1)}{n_1} \quad (7)$$

In connection with this rule, the decision $\sigma_1^2/\sigma_0^2 < 1$ when in fact $\sigma_1^2/\sigma_0^2 \geq 1$ is an error of the first kind, whence the maximum value of the probability of an error of the first kind is α , which is the probability of the decision $\sigma_1^2/\sigma_0^2 < 1$ when $\sigma_1^2/\sigma_0^2 = 1$. Accordingly, the statistical test defined by (6) and (7) is said to be conducted at the α level of significance, although $\chi_{1-\alpha}^2(n_1)$ is the 100(1 - α) percentage point of χ^2 for n_1 degrees of freedom.

The value of $\rho' = \sigma_1^2/\sigma_0^2$ for which the probability of a decision $\sigma_1^2/\sigma_0^2 \geq 1$ equals β when the test specified by inequalities (6) and (7) is employed is readily shown to be

$$\begin{aligned} \rho'(\alpha, \beta, n_1) &= \frac{\chi_{1-\alpha}^2(n_1)}{\chi_{\beta}^2(n_1)} \\ &= \frac{1}{\rho(\beta, \alpha, n_1)} \end{aligned} \quad (8)$$

Consequently, values of ρ' are found by interchanging α and β and taking the reciprocal of the corresponding ρ . Thus

$$\rho'(0.05, 0.05, n_1) = \frac{1}{\rho(0.05, 0.05, n_1)} \quad (9)$$

and

$$\rho'(0.01, 0.05, n_1) = \frac{1}{\rho(0.05, 0.01, n_1)} \quad (10)$$

can be obtained from Table 8.1 by taking reciprocals of the relevant entries; and values of

$$\rho'(0.01, 0.01, n_1) = \frac{1}{\rho(0.01, 0.01, n_1)} \quad (11)$$

and

$$\rho'(0.05, 0.01, n_1) = \frac{1}{\rho(0.01, 0.05, n_1)} \quad (12)$$

can be obtained in similar manner from Table 8.2.

3.2. Illustration

Example IV. The scores of students taking a standard examination have a standard deviation of 20 points ($\sigma_0 = 20$). An untried examination will be acceptable if with it students' scores have a standard deviation not less than 20 points ($\sigma_1^2/\sigma_0^2 \geq 1$), and the authorities are willing to accept a risk of 0.05 ($\alpha = 0.05$) of erroneously rejecting an examination for which $\sigma_1 = \sigma_0 = 20$. On the other hand, acceptance of an examination for which $\sigma_1 = 10$ ($\rho' = 1/4$) would be a serious error, and it is desired to hold the risk of such an occurrence below 0.01. How many students will be needed in a preliminary tryout of the examination?

For $\alpha = 0.05$ and $\beta = 0.01$, we seek the value of n_1 for which $\rho'(0.05, 0.01, n_1)$ is 0.25, that is, the value n_1 for which $\rho(0.01, 0.05, n_1)$ is 4. In Table 8.2 we see that

$$\rho(0.01, 0.05, 16) = 4.0193 \quad (13)$$

$$\rho(0.01, 0.05, 17) = 3.8526 \quad (14)$$

Accordingly, $n_1 \geq 17$ will be required, which means that the smallest number of students ($n_1 + 1$) that will suffice is 18.

4. EXPERIMENTS TO DETERMINE WHETHER A PARTICULAR ONE OF TWO NEW PRODUCTS IS MORE VARIABLE THAN THE OTHER

4.1. Problem

When the variance of the measurable characteristic is unknown for both products, as it generally is when both are new, the rules of procedure given in Secs. 2 and 3 cannot be applied. Let σ_1^2 denote the true variance of the measurable characteristic in the case of product I, let σ_2^2 denote the variance in the case of product II, and let s_1^2 and s_2^2 denote estimates of σ_1^2 and σ_2^2 computed from measurements on I and II, respectively. A choice between the conclusion $\sigma_1^2/\sigma_2^2 \leq 1$ and the conclusion $\sigma_1^2/\sigma_2^2 > 1$ can then be based on the observed values of s_1^2 and s_2^2 , for example, on the observed value of their ratio s_1^2/s_2^2 . That is, it may be agreed in advance that either the conclusion $\sigma_1^2/\sigma_2^2 > 1$ or the conclusion $\sigma_1^2/\sigma_2^2 \leq 1$ will be accepted according as s_1^2/s_2^2 exceeds or does not exceed some number C chosen in advance.

In selecting C it is necessary to distinguish between the following two situations: (1) For various reasons (for example, cost, convenience, and so forth) product I is preferred a priori and should be chosen unless σ_1^2 is substantially larger than σ_2^2 . (2) Product II is to be chosen if $\sigma_1^2 > \sigma_2^2$, but it is immaterial which is chosen when $\sigma_1^2 = \sigma_2^2$.

4.2. Standard Procedure When Product I Is to Be Chosen Unless σ_1^2 Is Larger Than σ_2^2

4.2.1. Procedure.—The standard procedure in case (1) is to compute from the data estimates s_1^2 and s_2^2 such that in repeated sampling $n_1 s_1^2 / \sigma_1^2$ and $n_2 s_2^2 / \sigma_2^2$ will be distributed independently as χ^2 for n_1 and n_2 degrees of freedom, respectively, and to base the choice on the following rule:

(a) Accept product I whenever

$$\frac{s_1^2}{s_2^2} \leq F_\alpha(n_1, n_2) \quad (15)$$

(b) Accept product II whenever

$$\frac{s_1^2}{s_2^2} > F_\alpha(n_1, n_2) \quad (16)$$

where $F_\alpha(n_1, n_2)$ is the α level of significance of the variance ratio distribution

$$\begin{aligned} \alpha &= P\{F(n_1, n_2) > F_\alpha(n_1, n_2)\} \\ &= \frac{\Gamma\left(\frac{n_1 + n_2}{2}\right)}{\Gamma\left(\frac{n_1}{2}\right) \Gamma\left(\frac{n_2}{2}\right)} \left(\frac{n_1}{n_2}\right)^{\frac{n_1}{2}} \int_{F_\alpha(n_1, n_2)}^{\infty} \frac{F^{\frac{n_1-2}{2}} dF}{\left(1 + \frac{n_1 F}{n_2}\right)^{\frac{n_1+n_2}{2}}} \quad (17) \end{aligned}$$

Since, under the assumptions regarding the distribution of s_1^2 and s_2^2 , the ratio $(s_1^2/\sigma_1^2)/(s_2^2/\sigma_2^2)$ is distributed as F for n_1 and n_2 degrees of freedom whatever the values of σ_1^2 and σ_2^2 , it is clear from (17) that the probability of (16) occurring when $\sigma_1^2 = \sigma_2^2$ is exactly α .

Accordingly, if choosing product II when its variability is not less than that of product I (that is, when $\sigma_1^2/\sigma_2^2 \leq 1$) is termed an error of the first kind, clearly α is the maximum value of the probability of an error of the first kind when the standard procedure is followed and the distributions of s_1^2 and s_2^2 are as assumed. The test is thus said to be conducted at the α level of significance.

Let the true value of the ratio σ_1^2/σ_2^2 be denoted by

$$\phi = \frac{\sigma_1^2}{\sigma_2^2} \quad (18)$$

Then it is of interest to determine the value of ϕ for which the probability is β that product I will be chosen by application of (15) and (16). The answer is readily found from the relation*

* Shortly after this formula was derived, a British document was received in which essentially the same formula is given and attributed to D. V. Lindley; see BAINES, *Economical Design*,

$$\begin{aligned}\phi(\alpha, \beta, n_1, n_2) &= \frac{F_\alpha(n_1, n_2)}{F_{1-\beta}(n_1, n_2)} \\ &= F_\alpha(n_1, n_2) \cdot F_\beta(n_2, n_1)\end{aligned}\quad (19)$$

Extensive tables of $\phi(\alpha, \beta, n_1, n_2)$ corresponding to $\alpha = 0.05$ and 0.01 and to a range of values of β , n_1 , and n_2 are presented as Tables 8.3 and 8.4, pp. 284–295 and 298–309. The use of formula (19) in the computation of these tables is explained in Sec. 6, which also includes a discussion of methods of interpolation. Figures 8.3 and 8.4 show the operating-characteristic curves plotted from the tables, for $n_1 = n_2 = 5, 10, 15, 20, 30, 40, 60, 120$.

4.2.2. Two Special Cases.—Before illustrating the use and interpretation of Tables 8.3 and 8.4, we may notice two important special cases involving $n_1 = n_2$:

(a) When $n_1 = n_2 = n$ and $\beta = 0.50$

$$F_{0.50}(n, n) = 1 \quad (20)$$

for all values of n , whence

$$\phi(\alpha, 0.50, n, n) = F_\alpha(n, n) \quad (21)$$

In other words, when the degrees of freedom for s_1^2 and s_2^2 are equal, the probability of an error of the second kind is $1/2$ when $\sigma_1^2/\sigma_2^2 = F_\alpha(n, n)$, the critical ratio employed in the test. Thus $F_\alpha(n, n)$ may be termed the indifference value of σ_1^2/σ_2^2 , that is, the value of σ_1^2/σ_2^2 for which the test is equally likely to select either product.

(b) When $n_1 = n_2 = n$ and $\beta = \alpha$

$$\phi(\alpha, \alpha, n, n) = F_\alpha(n, n) \quad (22)$$

In other words, when the degrees of freedom for s_1^2 and s_2^2 are equal, the probability of an error of the second kind is α when σ_1/σ_2 , the ratio of the true standard deviations, equals $F_\alpha(n, n)$, the critical ratio employed in the test. That is, the risk of an error of the second kind when $\sigma_1/\sigma_2 = F_\alpha(n, n)$ is the same as the risk of an error of the first kind when $\sigma_1/\sigma_2 = 1$.

4.2.3. Illustrations

Example V. A choice between two products is to be made, the relative variability of the two products being relevant but of secondary importance in the sense that it is immaterial which is chosen if $\sigma_1^2/\sigma_2^2 = 2$, product I being preferred if $\sigma_1^2/\sigma_2^2 < 2$, product II if $\sigma_1^2/\sigma_2^2 > 2$. If the choice is to be based on (15) and (16), using the 0.05 level of significance ($\alpha = 0.05$), and if s_1^2 and s_2^2 are to be based on an equal number ($n_1 = n_2 = n$) degrees of freedom, how many degrees of freedom will be needed for each, and for what value of

σ_1^2/σ_2^2 is the probability 0.95 that product II will be chosen ($\beta = 0.05$)?

From the first special case of Sec. 4.2.2, we have

$$\phi(0.05, 0.50, n, n) = F_{0.05}(n, n),$$

and from tables of the F distribution we find this to be 1.9838 when $n = 24$. Thus, if 24 degrees of freedom are used for each product, the probability that product II will be chosen is 0.05 if $\sigma_1^2/\sigma_2^2 = 1$, 0.50 if $\sigma_1^2/\sigma_2^2 = 2$, and (according to case (b) of Sec 4.2.2) 0.95 if $\sigma_1^2/\sigma_2^2 = 4$.

Example VI. If only 30 degrees of freedom are available for s_1^2 and if a test is conducted at the 0.05 level of significance, how many degrees of freedom will be needed for s_2^2 in order to ensure that the probability is only 0.05 of product I being chosen when $\sigma_1/\sigma_2 = 1.5$?

The desired stringency cannot be achieved, since Table 8.3 shows $\phi(0.05, 0.05, 30, \infty) = 2.367$, which exceeds $\sigma_1^2/\sigma_2^2 = 2.25$.

4.3. Procedure When It Is Immaterial Which Product Is Chosen If $\sigma_1^2 = \sigma_2^2$

This situation arises when variability is the primary basis for choosing between two products. The following rule is appropriate to this situation:

(a) Accept product I whenever

$$\frac{s_1^2}{s_2^2} \leq F_{0.50}(n_1, n_2) \quad (23)$$

(b) Accept product II whenever

$$\frac{s_1^2}{s_2^2} > F_{0.50}(n_1, n_2) \quad (24)$$

where $F_{0.50}(n_1, n_2)$ is the median of the F distribution for n_1 and n_2 degrees of freedom. Note that $F_{0.50}(n_1, n_2) \neq 1$ unless $n_1 = n_2$.

By setting $\alpha = 0.50$ in (19), it is readily seen that when the choice is based on (23) and (24) the probability is β that product I will be chosen if

$$\frac{\sigma_1^2}{\sigma_2^2} = \phi(0.50, \beta, n_1, n_2) = \frac{F_{0.50}(n_1, n_2)}{F_{1-\beta}(n_1, n_2)} \quad (25)$$

Conversely, the probability is β that product II will be chosen when

$$\frac{\sigma_1^2}{\sigma_2^2} = \phi(0.50, 1 - \beta, n_1, n_2) = \frac{F_{0.50}(n_1, n_2)}{F_{\beta}(n_1, n_2)} \quad (26)$$

TABLE 8.3
VALUES OF $\phi(0.05, \beta, n_1, n_2)$ CORRESPONDING TO SELECTED VALUES OF β , n_1 , AND n_2
 $\beta = 0.005$

$n_1 \backslash n_2$	1	2	3	4	5	6	7	8	9	10	12	15	20	24	30	40	60	120	∞
1	2617000	306000	11980	7037	5244	4369	3844	3509	3275	3102	2867	2656	2466	2370	2296	2217	2142	2071	2004
2	3703000	3781	964	505	353	281	240	213	195	182	165	149	135	129	123	118	112	107	103
3	2189000	1902	440	221	149	115	96	84	76	70	63	56	50	47	45	42	40	38	36
4	1730000	1384	364	147	97	74	61	53	49	47	43	39	36	34	32	30	28	26	25
5	1524000	1153	245	116	75	56	43	38	35	33	30	28	26	24	23	21	20	18	17
6	1403000	1025	213	99	63	47	38	32	29	26	23	21	19	17	16	14	13	12	11
7	1329000	944	193	89	58	41	33	28	25	22	19	17	15	14	12	11	10	9	8
8	1272000	889	179	81	51	37	30	25	22	20	17	15	13	12	11	10	9	8	7
9	1233000	845	166	76	47	33	28	23	20	18	15	13	11	10	9	8	7	6	5
10	1203000	818	162	72	45	32	28	22	19	17	14	12	10	9	8	7	6	5	4
12	1169000	774	151	67	41	30	26	21	18	16	13	11	9	8	7	6	5	4	3
15	1110000	734	141	62	38	27	23	19	16	14	11	9	7	6	5	4	3	2	1
20	1081000	698	132	57	34	24	20	16	13	12	9	7	5	4	3	2	1	0	0
24	1062000	678	128	53	31	22	18	15	12	11	8	6	4	3	2	1	0	0	0
30	1045000	651	124	50	29	20	16	13	11	10	7	5	3	2	1	0	0	0	0
40	1027000	644	120	47	27	19	15	12	10	9	6	4	2	1	0	0	0	0	0
60	1010000	628	116	45	26	18	14	11	9	8	5	3	2	1	0	0	0	0	0
120	99410	612	112	44	25	17	13	10	8	7	4	2	1	0	0	0	0	0	0
∞	97820	597	109	43	24	16	12	9	7	6	3	2	1	0	0	0	0	0	0

Explanation

Let (c) n_1 be an estimate of σ^2 such that $\frac{n_1 n_2}{\sigma_1^2}$ is distributed as χ^2 for n_1 degrees of freedom

(b) n_2 be an estimate of σ_2^2 such that $\frac{n_2 n_1}{\sigma_2^2}$ is distributed independently as χ^2 for n_2 degrees of freedom

(c) $F(n_1, n_2)$ be the value of the variance ratio for n_1 and n_2 degrees of freedom exceeded with probability ϵ

(d) the decision $\frac{\sigma_1^2}{\sigma_2^2} > 1$, or the decision $\frac{\sigma_1^2}{\sigma_2^2} \leq 1$, be made according as $\frac{n_1^2}{n_2^2}$ exceeds or does not exceed $F_0 \phi(n_1, n_2)$

Then the probability is β that the decision $\frac{\sigma_1^2}{\sigma_2^2} \leq 1$ will be made when $\frac{\sigma_1^2}{\sigma_2^2} = \phi(0.05, \beta, n_1, n_2) = F_0 \phi(n_1, n_2) = F_0 \phi(n_1, n_2) \cdot F_0 \phi(n_1, n_2)$.

TABLE 8.3

COMPARING TWO STANDARD DEVIATIONS

285

 $\beta = 0.01$

m	1	2	3	4	5	6	7	8	9	10	12	15	20	24	30	40	60	120	∞
1	654200	19650	7350	4761	3742	3216	2803	2590	2540	2429	2276	2136	2008	1945	1891	1837	1785	1735	1687
2	92560	1881	590.6	346.4	255.1	211.2	184.8	167.5	155.5	146.6	134.5	123.5	113.7	109.2	104.5	100.8	96.95	93.27	89.78
3	54720	947.2	273.3	152.2	108.7	87.43	75.11	67.14	61.61	57.57	52.05	47.14	42.77	40.76	38.86	37.06	35.37	33.76	32.24
4	43360	699.2	189.2	102.1	71.27	56.38	47.82	42.32	38.52	35.75	31.99	28.68	25.71	24.30	23.09	21.89	20.76	19.69	18.68
5	39060	574.6	152.7	80.59	55.86	43.29	36.36	31.95	28.61	26.69	23.68	21.04	18.70	17.63	16.63	15.68	14.80	13.96	13.17
6	35080	510.9	132.8	68.94	46.82	36.27	30.25	26.42	23.28	21.87	19.28	17.01	15.00	14.09	13.23	12.42	11.66	10.95	10.28
7	31150	470.7	120.3	61.71	41.53	31.93	26.48	23.02	20.64	18.91	16.58	14.54	12.74	11.92	11.16	10.43	9.758	9.122	8.524
8	31810	443.1	111.8	56.90	37.94	29.01	23.94	20.73	18.42	16.62	14.78	12.89	11.23	10.48	9.770	9.107	8.485	7.901	7.362
9	30950	423.0	105.6	53.26	35.37	26.91	22.12	19.09	17.01	15.51	13.48	11.71	10.15	9.444	8.782	8.160	7.577	7.030	6.516
10	30060	407.8	101.0	50.59	33.43	25.33	20.76	17.86	15.88	14.44	12.51	10.82	9.343	8.672	8.042	7.452	6.898	6.378	5.890
12	28900	386.3	94.42	46.85	30.71	23.12	18.65	16.14	14.29	12.96	11.16	9.594	8.219	7.596	7.012	6.465	5.951	5.469	5.017
15	27070	366.1	86.34	43.58	29.21	21.09	17.09	14.56	12.84	11.59	9.823	8.466	7.187	6.509	6.067	5.558	5.081	4.633	4.211
20	27020	347.4	82.70	40.18	25.60	19.22	15.47	13.11	11.50	10.34	8.788	7.429	6.240	5.702	5.197	4.723	4.278	3.858	3.462
24	26560	338.4	80.03	38.67	24.81	18.34	14.73	12.43	10.83	9.739	8.254	6.943	5.795	5.275	4.787	4.329	3.897	3.490	3.104
30	26110	329.8	77.46	37.22	23.76	17.50	13.99	11.78	10.28	9.193	7.742	6.476	5.367	4.864	4.392	3.948	3.529	3.131	2.752
40	25680	321.5	74.97	35.82	22.78	16.69	13.29	11.15	9.700	8.652	7.251	6.027	4.955	4.468	4.011	3.579	3.170	2.779	2.403
60	25260	313.4	72.88	34.47	21.79	15.91	12.62	10.55	9.146	8.134	6.779	5.596	4.559	4.086	3.641	3.220	2.817	2.429	2.048
120	24850	305.6	70.28	33.18	20.87	15.16	11.97	9.973	8.614	7.635	6.325	5.181	4.175	3.715	3.291	2.867	2.467	2.072	1.681
∞	24450	298.1	68.05	31.93	19.87	14.44	11.35	9.418	8.103	7.166	5.889	4.780	3.802	3.354	2.927	2.510	2.110	1.733	1.360

For explanation see the panel of this table for $\beta = 0.005$

TABLE 8.3.— $\phi(0.05, \beta, n_1, n_2)$.—(Continued)
 $\beta = 0.025$

n_1 n_2	1	2	3	4	5	6	7	8	9	10	12	15	20	24	30	40	60	120	∞
1	104900.	7682.	3763	2744.	2303	2062	1911.	1809	1734	1678	1599.	1525.	1455.	1424.	1392.	1362	1333.	1305	1278.
2	14930.	741.0	307.5	205.0	162.7	140.3	126.6	117.4	110.8	105.8	98.63	92.58	86.75	84.02	81.36	78.83	76.46	74.14	71.92
3	8782.	374.1	143.2	90.98	69.88	59.00	52.34	47.91	44.75	42.40	39.13	36.13	33.42	32.14	30.93	29.78	28.65	27.50	26.57
4	6935.	272.5	99.84	61.30	45.22	38.38	33.06	30.52	28.30	26.65	24.33	22.28	20.39	19.51	18.67	17.87	17.11	16.38	15.68
5	6041.	227.4	80.52	48.82	36.09	29.64	25.77	23.21	21.40	20.06	18.20	16.52	14.99	14.23	13.61	12.96	12.35	11.76	11.20
6	5611.	202.3	70.10	41.70	30.61	24.83	21.53	19.29	17.71	16.53	14.91	13.45	12.12	11.50	10.92	10.36	9.826	9.319	8.835
7	5302.	186.4	63.57	37.30	27.22	22.02	18.92	16.87	15.43	14.36	12.89	11.56	10.36	9.801	9.270	8.768	8.283	7.825	7.398
8	5087.	175.6	59.12	34.46	24.92	20.05	17.15	15.24	13.90	12.90	11.53	10.29	9.176	8.657	8.164	7.695	7.248	6.822	6.417
9	4920.	167.7	55.90	32.35	23.26	18.63	15.88	14.07	12.80	11.89	10.56	9.337	8.329	7.839	7.373	6.929	6.506	6.104	5.721
10	4800.	161.6	53.47	30.76	22.01	17.57	14.93	13.19	11.97	11.07	9.827	8.706	7.694	7.225	6.779	6.355	5.960	5.585	5.198
12	4637.	153.1	50.04	28.52	20.26	16.05	13.59	11.96	10.82	9.970	8.905	7.755	6.904	6.367	5.940	5.541	5.172	4.810	4.465
15	4474.	145.2	46.86	26.45	18.65	14.70	12.36	10.83	9.754	8.958	7.865	6.879	5.989	5.376	5.154	4.810	4.453	4.112	3.786
20	4321.	137.8	43.90	24.53	17.16	13.43	11.23	9.787	8.774	8.027	6.998	6.072	5.255	4.847	4.476	4.123	3.765	3.461	3.149
24	4248.	134.3	42.30	23.03	16.45	12.83	10.70	9.296	8.313	7.588	6.591	5.692	4.879	4.502	4.142	3.797	3.467	3.149	2.843
30	4177.	130.9	41.15	22.76	15.78	12.26	10.18	8.835	7.871	7.167	6.200	5.327	4.537	4.160	3.818	3.481	3.158	2.845	2.541
40	4108.	127.6	39.58	21.92	15.13	11.71	9.691	8.372	7.446	6.762	5.823	4.975	4.206	3.848	3.504	3.174	2.855	2.545	2.238
60	4043.	124.4	38.39	21.11	14.50	11.18	9.217	7.930	7.037	6.373	5.460	4.635	3.897	3.536	3.199	2.874	2.557	2.245	1.929
120	3975.	121.3	37.38	20.33	13.90	10.67	8.762	7.537	6.644	5.990	5.111	4.308	3.576	3.233	2.901	2.578	2.259	1.937	1.590
∞	3912.	118.3	36.21	19.59	13.32	10.18	8.324	7.114	6.206	5.638	4.775	3.992	3.275	2.936	2.607	2.282	1.954	1.601	1.000

For explanation see the panel of this table for $\beta = 0.005$.

TABLE 8.3

COMPARING TWO STANDARD DEVIATIONS

287

 $\beta = 0.05$

$\frac{n_1}{n_2}$	1	2	3	4	5	6	7	8	9	10	12	15	20	24	30	40	60	120	∞
1	2670.	3693.	2185	1731.	1521	1401.	1324.	1270	1231.	1201.	1158.	1117.	1079.	1031.	1043.	1026.	1009.	992.8	977.0
2	3693.	381.0	183.1	133.7	111.6	99.42	91.63	86.38	82.51	79.58	75.43	71.84	67.92	66.20	64.53.	62.92	61.37	59.86	58.40
3	2185	183.1	96.06	60.10	48.76	42.53	38.63	35.97	34.04	32.53	30.52	28.61	26.83	25.99	25.18	24.40	23.64	22.91	22.21
4	1731.	133.7	90.70	40.91	32.49	27.94	25.11	23.18	21.79	20.74	19.27	17.90	16.63	15.03	15.45	14.90	14.30	13.85	13.35
5	1521.	111.6	48.76	32.48	25.51	21.72	19.38	17.77	16.62	15.75	14.53	13.40	12.36	11.86	11.39	10.93	10.49	10.07	9.665
6	1401.	99.42	42.53	27.94	21.72	18.35	16.25	14.85	13.93	13.06	11.98	10.89	10.07	9.635	9.218	8.816	8.430	8.058	7.699
7	1324.	91.63	38.63	25.11	19.38	16.26	14.34	13.04	12.11	11.40	10.41	9.502	8.659	8.262	7.890	7.513	7.159	6.818	6.491
8	1270.	86.38	35.97	23.18	17.77	14.85	13.04	11.82	10.94	10.28	9.355	8.499	7.709	7.337	6.979	6.634	6.302	5.982	5.675
9	1231.	82.51	34.04	21.79	16.62	13.83	12.11	10.94	10.11	9.476	8.593	7.779	7.026	6.672	6.331	6.002	5.686	5.382	5.088
10	1201.	79.58	32.68	20.74	15.75	13.06	11.40	10.23	9.476	8.870	8.021	7.237	6.513	6.172	5.844	5.527	5.223	4.929	4.646
12	1158.	75.43	30.52	19.27	14.53	11.98	10.41	9.355	8.593	8.021	7.218	6.478	5.783	5.471	5.180	4.890	4.611	4.341	4.083
15	1117.	71.84	28.61	17.90	13.40	10.98	9.502	8.499	7.779	7.237	6.478	5.777	5.128	4.822	4.537	4.242	3.967	3.701	3.442
20	1079	67.92	26.83	16.63	12.36	10.07	8.639	7.709	7.026	6.513	5.793	5.128	4.512	4.221	3.939	3.656	3.402	3.145	2.895
24	1061	66.20	25.99	16.03	11.86	9.635	8.262	7.337	6.672	6.172	5.444	4.822	4.221	3.935	3.650	3.382	3.132	2.879	2.630
30	1043	64.53	25.18	15.45	11.39	9.218	7.890	6.979	6.331	5.844	5.160	4.571	3.938	3.660	3.389	3.126	2.869	2.617	2.367
40	1026	62.92	24.40	14.90	10.83	8.816	7.513	6.634	6.002	5.527	4.860	4.242	3.660	3.382	3.126	2.866	2.610	2.357	2.103
60	1009	61.37	23.64	14.36	10.49	8.430	7.159	6.302	5.686	5.223	4.571	3.937	3.402	3.132	2.869	2.610	2.354	2.097	1.831
120	992.8	59.86	22.91	13.85	10.07	8.058	6.818	5.982	5.382	4.929	4.263	3.701	3.145	2.879	2.617	2.357	2.097	1.828	1.532
∞	977.0	58.40	22.21	13.35	9.665	7.699	6.491	5.675	5.088	4.646	4.023	3.442	2.895	2.630	2.367	2.103	1.831	1.532	1.000

For explanation see the preface of this table for $\beta = 0.05$.

TABLE 8.3. $-\phi(0.05, \beta, n_1, n_2)$.—(Continued) $\beta = 0.10$

n_1 n_2	1	2	3	4	5	6	7	8	9	10	12	15	20	24	30	40	60	120	∞
1	6436.	1701.	1195.	1021.	934.5	883.5	849.9	826.0	808.3	794.6	774.8	755.9	737.8	729.0	720.4	712.1	704.0	695.9	688.1
2	916.4	171.0	104.7	83.24	72.83	66.95	63.04	60.30	58.28	56.72	54.49	52.37	50.35	49.58	48.44	47.52	46.82	46.74	44.89
3	642.8	87.51	50.01	36.21	32.62	29.40	27.32	25.88	24.79	23.96	22.78	21.67	20.61	20.11	19.61	19.13	18.66	18.21	17.77
4	430.4	64.19	35.22	26.24	22.02	19.60	18.04	16.95	16.15	15.54	14.46	13.98	13.05	12.67	12.31	11.95	11.61	11.27	10.95
5	378.2	53.77	28.72	21.00	17.43	15.38	14.08	13.14	12.46	11.94	11.30	10.50	9.837	9.521	9.213	8.913	8.622	8.339	8.063
6	348.5	47.98	25.14	18.18	14.94	13.09	11.89	11.06	10.46	9.990	9.324	8.698	8.102	7.818	7.541	7.273	7.011	6.787	6.565
7	329.4	44.29	22.80	16.39	13.38	11.65	10.55	9.777	9.211	8.776	8.160	7.577	7.026	6.762	6.503	6.255	6.012	5.775	5.545
8	316.1	41.77	21.38	15.18	12.31	10.68	9.632	8.902	8.367	7.957	7.371	6.818	6.296	6.040	5.802	5.585	5.324	5.109	4.890
9	306.3	39.63	20.24	14.30	11.68	9.970	8.972	8.272	7.757	7.364	6.802	6.271	5.770	5.529	5.285	5.067	4.844	4.628	4.416
10	298.8	38.53	19.40	13.63	10.87	9.440	8.474	7.798	7.298	6.917	6.373	5.859	5.372	5.139	4.912	4.690	4.473	4.253	4.037
12	288.2	36.55	18.20	12.70	10.15	8.703	7.773	7.127	6.632	6.289	5.769	5.279	4.814	4.590	4.372	4.156	3.932	3.748	3.549
15	278.1	34.70	17.10	11.82	9.394	8.012	7.124	6.507	6.034	5.707	5.210	4.740	4.294	4.079	3.870	3.654	3.464	3.266	3.072
20	268.6	32.98	16.06	11.02	8.693	7.372	6.523	5.933	5.499	5.167	4.691	4.240	3.810	3.603	3.400	3.200	3.004	2.811	2.618
24	264.1	32.16	15.67	10.64	8.361	7.099	6.289	5.723	5.337	5.003	4.545	4.093	3.681	3.476	3.276	3.078	2.883	2.690	2.497
30	259.7	31.39	15.10	10.27	8.042	6.777	6.005	5.463	5.084	4.749	4.298	3.773	3.358	3.156	2.957	2.761	2.567	2.373	2.177
40	255.4	30.59	14.68	9.912	7.734	6.497	5.751	5.148	4.771	4.428	3.979	3.551	3.141	2.942	2.744	2.549	2.353	2.156	1.964
60	251.3	29.83	14.21	9.560	7.437	6.226	5.417	4.835	4.466	4.119	3.670	3.256	2.841	2.648	2.451	2.256	2.059	1.861	1.668
120	247.2	29.13	13.78	9.236	7.151	5.965	5.202	4.620	4.259	3.917	3.468	3.058	2.648	2.458	2.263	2.068	1.871	1.673	1.478
∞	243.3	28.43	13.37	8.920	6.876	5.713	4.965	4.414	4.059	3.717	3.268	2.855	2.452	2.262	2.067	1.872	1.675	1.477	1.281

For explanation see the panel of this table for $\beta = 0.005$.

TABLE 8.3

COMPARING TWO STANDARD DEVIATIONS

289

 $\beta = 0.25$

n_1	n_2	1	2	3	4	5	6	7	8	9	10	12	15	20	24	30	40	60	120	∞
1	941.0	513.0	436.6	405.9	389.5	379.4	372.5	367.5	363.7	360.6	358.4	352.2	348.1	346.1	344.1	342.2	340.3	338.4	335.5	333.5
2	138.8	57.00	43.60	38.49	35.75	34.06	32.92	32.10	31.47	30.99	30.27	29.58	28.92	28.59	28.27	27.95	27.64	27.33	27.03	26.73
3	83.05	30.12	21.85	18.66	16.98	15.95	15.26	14.76	14.33	14.03	13.65	13.23	12.82	12.63	12.43	12.24	12.05	11.86	11.68	11.50
4	66.15	22.44	15.75	13.19	11.84	11.01	10.46	10.05	9.750	9.513	9.165	8.828	8.502	8.342	8.184	8.030	7.876	7.726	7.577	7.428
5	58.28	18.98	13.03	10.76	9.569	8.537	8.343	7.986	7.717	7.507	7.199	6.890	6.609	6.467	6.327	6.188	6.052	5.917	5.784	5.651
6	53.79	17.04	11.52	9.415	8.312	7.034	7.176	6.843	6.596	6.401	6.114	5.835	5.565	5.433	5.302	5.173	5.045	4.919	4.794	4.669
7	50.80	15.80	10.56	8.566	7.520	6.877	6.442	6.122	5.891	5.705	5.432	5.187	4.909	4.782	4.657	4.533	4.411	4.289	4.170	4.051
8	48.86	14.95	9.907	7.955	6.978	6.350	5.940	5.637	5.403	5.229	4.965	4.709	4.459	4.336	4.214	4.094	3.975	3.857	3.740	3.625
9	47.40	14.33	9.429	7.562	6.584	5.983	5.576	5.280	5.057	4.883	4.626	4.379	4.131	4.011	3.892	3.774	3.657	3.540	3.425	3.313
10	46.27	13.86	9.066	7.241	6.266	5.697	5.298	5.010	4.791	4.620	4.368	4.123	3.882	3.764	3.646	3.530	3.414	3.299	3.185	3.073
12	44.65	13.18	8.553	6.768	5.803	5.294	4.907	4.627	4.415	4.243	4.004	3.764	3.529	3.413	3.297	3.183	3.068	2.955	2.841	2.730
15	43.13	12.56	8.071	6.365	5.469	4.917	4.542	4.270	4.064	3.902	3.662	3.423	3.197	3.083	2.969	2.855	2.741	2.627	2.513	2.402
20	41.69	11.97	7.623	5.970	5.102	4.569	4.201	3.937	3.735	3.577	3.343	3.113	2.885	2.771	2.659	2.544	2.429	2.313	2.199	2.089
24	41.00	11.69	7.409	5.782	4.927	4.399	4.040	3.778	3.576	3.422	3.191	2.962	2.735	2.621	2.508	2.393	2.277	2.160	2.049	1.939
30	40.33	11.42	7.203	5.601	4.750	4.226	3.863	3.625	3.423	3.273	3.043	2.815	2.589	2.475	2.361	2.245	2.127	2.007	1.892	1.781
40	39.83	11.15	7.004	5.426	4.596	4.082	3.732	3.498	3.292	3.142	2.912	2.685	2.459	2.345	2.231	2.115	2.000	1.883	1.771	1.661
60	39.05	10.90	6.812	5.257	4.439	3.932	3.585	3.353	3.146	2.997	2.767	2.541	2.315	2.201	2.087	1.971	1.856	1.743	1.631	1.521
120	38.43	10.65	6.625	5.093	4.287	3.780	3.443	3.183	3.002	2.850	2.624	2.398	2.172	2.058	1.943	1.828	1.714	1.601	1.489	1.379
∞	37.84	10.41	6.445	4.935	4.130	3.645	3.306	3.056	2.868	2.717	2.492	2.265	2.039	1.913	1.788	1.658	1.512	1.342	1.000	1.000

For explanation see the panel of this table for $\beta = 0.005$.

TABLE 8.3.— $\phi(0.05, \beta, n_1, n_2)$.—(Continued)
 $\beta = 0.50$

$n_1 \backslash n_2$	1	2	3	4	5	6	7	8	9	10	12	15	20	24	30	40	60	120	∞
1	161.5	133.0	120.0	123.2	121.5	120.5	119.7	119.2	118.8	118.5	118.0	117.5	117.0	116.8	116.6	116.4	116.1	115.9	115.7
2	27.77	19.00	10.89	15.94	15.41	15.07	14.84	14.86	14.53	14.42	14.26	14.11	13.96	13.88	13.81	13.73	13.66	13.59	13.51
3	17.31	10.84	9.277	8.575	8.178	7.920	7.740	7.607	7.508	7.425	7.304	7.186	7.095	7.011	6.933	6.850	6.838	6.781	6.724
4	14.95	8.382	7.063	6.385	6.035	5.805	5.644	5.525	5.434	5.361	5.253	5.145	5.085	4.995	4.933	4.850	4.828	4.775	4.723
5	12.51	7.244	5.963	5.383	5.050	4.834	4.682	4.569	4.482	4.413	4.309	4.207	4.104	4.053	4.002	3.951	3.901	3.849	3.799
6	11.63	6.956	5.671	5.113	4.793	4.584	4.437	4.327	4.242	4.175	4.073	3.973	3.872	3.820	3.772	3.722	3.671	3.621	3.570
7	11.06	6.180	4.931	4.449	4.130	3.931	3.787	3.679	3.596	3.529	3.430	3.330	3.230	3.180	3.130	3.080	3.029	2.979	2.925
8	10.66	5.892	4.728	4.196	3.898	3.687	3.545	3.438	3.356	3.290	3.191	3.091	2.991	2.941	2.891	2.841	2.790	2.739	2.685
9	10.36	5.650	4.539	4.011	3.707	3.495	3.367	3.261	3.179	3.113	3.014	2.915	2.816	2.765	2.715	2.664	2.613	2.561	2.509
10	10.14	5.513	4.388	3.870	3.560	3.347	3.231	3.126	3.044	2.978	2.880	2.780	2.680	2.630	2.579	2.528	2.476	2.424	2.371
13	9.815	5.253	4.178	3.668	3.371	3.176	3.077	2.982	2.891	2.825	2.733	2.637	2.537	2.486	2.435	2.381	2.329	2.275	2.220
15	9.569	5.071	3.991	3.479	3.186	2.992	2.894	2.800	2.708	2.642	2.550	2.454	2.354	2.301	2.250	2.197	2.143	2.088	2.032
20	9.220	4.866	3.794	3.301	3.011	2.819	2.681	2.577	2.494	2.430	2.330	2.228	2.124	2.071	2.016	1.960	1.903	1.844	1.782
24	9.082	4.763	3.708	3.216	2.927	2.736	2.598	2.494	2.413	2.347	2.246	2.144	2.039	1.984	1.928	1.871	1.812	1.750	1.685
30	8.947	4.674	3.622	3.133	2.846	2.655	2.516	2.414	2.332	2.266	2.165	2.061	1.954	1.898	1.841	1.782	1.720	1.655	1.586
40	8.817	4.582	3.538	3.053	2.767	2.577	2.439	2.335	2.253	2.186	2.085	1.980	1.870	1.813	1.754	1.693	1.628	1.559	1.484
60	8.686	4.493	3.458	2.975	2.691	2.500	2.363	2.259	2.176	2.109	2.006	1.900	1.788	1.729	1.668	1.603	1.534	1.459	1.374
120	8.564	4.408	3.379	2.900	2.617	2.426	2.289	2.184	2.101	2.034	1.930	1.821	1.708	1.645	1.581	1.512	1.437	1.352	1.247
∞	8.444	4.322	3.303	2.826	2.544	2.354	2.217	2.112	2.028	1.960	1.854	1.743	1.624	1.560	1.492	1.418	1.333	1.228	1.090

For explanation see the panel of this table for $\beta = 0.005$.

TABLE 8.3

COMPARING TWO STANDARD DEVIATIONS

291

 $\beta = 0.75$

n_1 n_2	1	2	3	4	5	6	7	8	9	10	12	15	20	24	30	40	60	120	∞
1	27.70	26.60	26.31	26.17	26.10	26.05	26.01	25.99	25.97	25.95	25.93	25.91	25.88	25.87	25.86	25.85	25.84	25.83	25.82
2	7.200	6.333	6.077	5.955	5.883	5.836	5.803	5.778	5.759	5.744	5.721	5.698	5.675	5.664	5.653	5.642	5.631	5.620	5.609
3	5.004	4.190	3.938	3.815	3.741	3.692	3.657	3.630	3.610	3.594	3.569	3.545	3.520	3.508	3.496	3.483	3.471	3.458	3.446
4	4.265	3.472	3.221	3.095	3.019	2.965	2.931	2.904	2.882	2.865	2.839	2.812	2.786	2.773	2.759	2.746	2.732	2.719	2.705
5	3.904	3.123	2.871	2.743	2.665	2.613	2.575	2.546	2.524	2.505	2.478	2.450	2.422	2.408	2.393	2.379	2.364	2.350	2.335
6	3.693	2.919	2.666	2.537	2.458	2.404	2.365	2.335	2.312	2.293	2.264	2.235	2.205	2.190	2.175	2.160	2.144	2.128	2.112
7	3.554	2.785	2.532	2.402	2.321	2.266	2.226	2.195	2.172	2.152	2.122	2.092	2.061	2.045	2.029	2.013	1.997	1.980	1.963
8	3.457	2.691	2.437	2.306	2.225	2.169	2.128	2.097	2.072	2.052	2.022	1.990	1.958	1.942	1.925	1.908	1.891	1.874	1.856
9	3.384	2.622	2.368	2.235	2.153	2.097	2.055	2.023	1.998	1.978	1.945	1.914	1.881	1.864	1.847	1.829	1.811	1.793	1.774
10	3.329	2.568	2.314	2.181	2.098	2.041	1.999	1.966	1.941	1.920	1.885	1.855	1.821	1.803	1.786	1.767	1.749	1.729	1.710
12	3.249	2.491	2.236	2.102	2.018	1.960	1.917	1.884	1.858	1.836	1.803	1.769	1.733	1.715	1.698	1.678	1.656	1.636	1.615
15	3.172	2.415	2.160	2.025	1.941	1.883	1.839	1.805	1.778	1.755	1.721	1.685	1.648	1.628	1.608	1.587	1.568	1.543	1.520
20	3.100	2.349	2.092	1.956	1.870	1.809	1.764	1.729	1.701	1.678	1.642	1.604	1.564	1.543	1.522	1.499	1.475	1.450	1.424
24	3.065	2.316	2.059	1.922	1.835	1.773	1.728	1.692	1.663	1.640	1.603	1.564	1.523	1.501	1.479	1.455	1.430	1.403	1.375
30	3.031	2.283	2.026	1.888	1.800	1.738	1.692	1.656	1.627	1.603	1.565	1.525	1.482	1.459	1.436	1.411	1.384	1.355	1.324
40	2.998	2.251	1.994	1.855	1.767	1.704	1.657	1.620	1.591	1.566	1.527	1.486	1.441	1.417	1.392	1.365	1.337	1.305	1.270
60	2.905	2.220	1.962	1.824	1.734	1.671	1.623	1.586	1.555	1.530	1.490	1.447	1.401	1.375	1.349	1.320	1.288	1.252	1.211
120	2.834	2.190	1.932	1.792	1.702	1.638	1.590	1.551	1.520	1.494	1.453	1.409	1.360	1.333	1.304	1.272	1.237	1.195	1.141
∞	2.903	2.161	1.902	1.762	1.671	1.606	1.557	1.517	1.486	1.459	1.416	1.370	1.318	1.289	1.258	1.222	1.181	1.127	1.000

For explanation see the panel of this table for $\beta = 0.005$

TABLE 8.3— $\phi(0.05, \beta, n_1, n_2)$ —(Continued)
 $\beta = 0.90$

n_1 n_2	1	2	3	4	5	6	7	8	9	10	12	15	20	24	30	40	60	120	∞
1	4.050	4.030	4.025	4.022	4.021	4.020	4.019	4.019	4.019	4.018	4.018	4.017	4.017	4.017	4.017	4.016	4.016	4.016	4.016
2	2.171	2.111	2.092	2.082	2.076	2.073	2.070	2.068	2.067	2.065	2.063	2.061	2.060	2.059	2.058	2.057	2.056	2.055	2.054
3	1.876	1.749	1.721	1.706	1.698	1.692	1.688	1.684	1.682	1.680	1.677	1.674	1.670	1.669	1.667	1.666	1.664	1.662	1.661
4	1.696	1.606	1.573	1.555	1.544	1.537	1.532	1.527	1.524	1.522	1.518	1.514	1.509	1.507	1.505	1.503	1.501	1.499	1.497
5	1.627	1.531	1.495	1.475	1.463	1.454	1.448	1.443	1.439	1.436	1.431	1.426	1.421	1.419	1.416	1.414	1.411	1.408	1.406
6	1.586	1.485	1.446	1.425	1.412	1.402	1.395	1.390	1.386	1.382	1.377	1.372	1.366	1.363	1.360	1.357	1.354	1.351	1.348
7	1.558	1.454	1.414	1.392	1.377	1.367	1.360	1.354	1.349	1.345	1.340	1.334	1.328	1.324	1.321	1.318	1.314	1.311	1.307
8	1.538	1.432	1.391	1.368	1.352	1.342	1.334	1.328	1.323	1.319	1.313	1.306	1.299	1.296	1.292	1.289	1.285	1.281	1.277
9	1.523	1.416	1.373	1.349	1.334	1.323	1.314	1.308	1.303	1.298	1.292	1.285	1.278	1.274	1.270	1.266	1.262	1.258	1.254
10	1.511	1.403	1.359	1.335	1.319	1.307	1.297	1.290	1.284	1.279	1.273	1.266	1.259	1.254	1.250	1.246	1.241	1.237	1.233
12	1.494	1.384	1.340	1.314	1.297	1.285	1.276	1.269	1.263	1.258	1.251	1.243	1.235	1.231	1.226	1.221	1.217	1.212	1.206
15	1.478	1.366	1.320	1.294	1.276	1.264	1.254	1.247	1.240	1.235	1.227	1.219	1.210	1.205	1.200	1.194	1.189	1.183	1.177
20	1.463	1.349	1.302	1.274	1.256	1.243	1.233	1.224	1.218	1.212	1.204	1.194	1.184	1.178	1.173	1.166	1.160	1.153	1.147
24	1.455	1.341	1.293	1.265	1.246	1.232	1.222	1.214	1.207	1.201	1.192	1.182	1.171	1.166	1.160	1.153	1.146	1.139	1.131
30	1.448	1.332	1.284	1.256	1.236	1.222	1.211	1.203	1.196	1.190	1.180	1.170	1.159	1.152	1.146	1.139	1.131	1.123	1.114
40	1.441	1.324	1.275	1.246	1.226	1.212	1.201	1.192	1.185	1.178	1.168	1.156	1.146	1.139	1.132	1.124	1.116	1.107	1.096
60	1.433	1.316	1.267	1.237	1.217	1.202	1.191	1.181	1.174	1.167	1.157	1.145	1.132	1.125	1.118	1.109	1.100	1.089	1.076
120	1.427	1.309	1.258	1.228	1.208	1.193	1.181	1.171	1.163	1.156	1.145	1.133	1.119	1.111	1.103	1.093	1.082	1.069	1.051
∞	1.420	1.301	1.250	1.220	1.199	1.183	1.171	1.161	1.152	1.145	1.134	1.121	1.106	1.097	1.087	1.076	1.063	1.045	1.000

For explanation see the panel of this table for $\beta = 0.05$.

TABLE 8.3

COMPARING TWO STANDARD DEVIATIONS

293

 $\beta = 0.975$

$n_1 \backslash n_2$	1	2	3	4	5	6	7	8	9	10	12	15	20	24	30	40	60	120	∞
1	0.2492	0.2495	0.2498	0.2499	0.2497	0.2497	0.2497	0.2497	0.2497	0.2497	0.2497	0.2497	0.2497	0.2497	0.2497	0.2497	0.2498	0.2498	0.2498
2	0.4808	0.4872	0.4903	0.4904	0.4910	0.4915	0.4918	0.4920	0.4922	0.4923	0.4925	0.4927	0.4930	0.4931	0.4931	0.4933	0.4934	0.4935	0.4936
3	0.5806	0.5854	0.5899	0.5907	0.5916	0.5920	0.5927	0.5933	0.5939	0.5943	0.5949	0.5956	0.5961	0.5965	0.5969	0.5973	0.5976	0.5979	0.5981
4	0.6300	0.6321	0.6345	0.6351	0.6358	0.6364	0.6371	0.6377	0.6383	0.6388	0.6394	0.6400	0.6406	0.6411	0.6416	0.6421	0.6426	0.6430	0.6433
5	0.6603	0.6611	0.6628	0.6631	0.6637	0.6641	0.6646	0.6651	0.6656	0.6661	0.6666	0.6671	0.6676	0.6681	0.6686	0.6691	0.6696	0.6700	0.6703
6	0.6704	0.6708	0.6719	0.6720	0.6727	0.6731	0.6736	0.6740	0.6744	0.6748	0.6753	0.6758	0.6763	0.6767	0.6771	0.6776	0.6781	0.6785	0.6788
7	0.6926	0.6928	0.6939	0.6941	0.6948	0.6953	0.6958	0.6963	0.6967	0.6971	0.6976	0.6981	0.6986	0.6990	0.6994	0.6999	0.7003	0.7007	0.7010
8	0.7024	0.7029	0.7038	0.7040	0.7047	0.7053	0.7058	0.7063	0.7067	0.7071	0.7076	0.7081	0.7086	0.7090	0.7094	0.7099	0.7103	0.7107	0.7110
9	0.7098	0.7101	0.7109	0.7111	0.7118	0.7124	0.7129	0.7134	0.7138	0.7143	0.7148	0.7153	0.7158	0.7162	0.7167	0.7171	0.7176	0.7180	0.7183
10	0.7157	0.7159	0.7165	0.7167	0.7174	0.7180	0.7185	0.7190	0.7194	0.7199	0.7204	0.7209	0.7214	0.7218	0.7223	0.7227	0.7232	0.7236	0.7239
12	0.7243	0.7244	0.7251	0.7252	0.7259	0.7265	0.7270	0.7275	0.7279	0.7284	0.7289	0.7294	0.7299	0.7303	0.7308	0.7312	0.7317	0.7321	0.7324
15	0.7328	0.7329	0.7336	0.7337	0.7344	0.7350	0.7355	0.7360	0.7364	0.7369	0.7374	0.7379	0.7384	0.7388	0.7393	0.7397	0.7402	0.7406	0.7409
20	0.7411	0.7412	0.7419	0.7420	0.7426	0.7432	0.7437	0.7442	0.7447	0.7452	0.7457	0.7462	0.7467	0.7471	0.7476	0.7481	0.7486	0.7490	0.7493
24	0.7451	0.7452	0.7459	0.7460	0.7466	0.7472	0.7477	0.7482	0.7487	0.7492	0.7497	0.7502	0.7507	0.7511	0.7516	0.7521	0.7526	0.7530	0.7533
30	0.7492	0.7493	0.7500	0.7501	0.7507	0.7513	0.7518	0.7523	0.7528	0.7533	0.7538	0.7543	0.7548	0.7552	0.7557	0.7562	0.7567	0.7571	0.7574
40	0.7531	0.7532	0.7539	0.7540	0.7546	0.7552	0.7557	0.7562	0.7567	0.7572	0.7577	0.7582	0.7587	0.7591	0.7596	0.7601	0.7606	0.7610	0.7613
60	0.7570	0.7571	0.7578	0.7579	0.7584	0.7590	0.7595	0.7600	0.7605	0.7610	0.7615	0.7620	0.7625	0.7629	0.7634	0.7639	0.7644	0.7648	0.7651
120	0.7608	0.7609	0.7616	0.7617	0.7623	0.7629	0.7634	0.7639	0.7644	0.7649	0.7654	0.7659	0.7664	0.7668	0.7673	0.7678	0.7683	0.7687	0.7690
∞	0.7646	0.7646	0.7653	0.7654	0.7660	0.7666	0.7671	0.7676	0.7681	0.7686	0.7691	0.7696	0.7701	0.7705	0.7710	0.7715	0.7720	0.7724	0.7727

For explanation see the panel of this table for $\beta = 0.005$.

TABLE 8.3— $\phi(0.05, \beta, n_1, n_2)$ —(Continued)
 $\beta = 0.99$

n_1 n_2	1	2	3	4	5	6	7	8	9	10	12	15	20	24	30	40	60	120	∞
1	0.03984	0.03900	0.03902	0.03903	0.03903	0.03904	0.03904	0.03904	0.03904	0.03904	0.03904	0.03904	0.03904	0.03905	0.03905	0.03905	0.03905	0.03905	0.03905
2	0.1879	0.1879	0.1883	0.1883	0.1883	0.1884	0.1884	0.1884	0.1884	0.1884	0.1884	0.1884	0.1884	0.1885	0.1885	0.1885	0.1885	0.1885	0.1885
3	0.2968	0.3100	0.3149	0.3176	0.3192	0.3203	0.3211	0.3218	0.3223	0.3227	0.3233	0.3239	0.3245	0.3248	0.3251	0.3254	0.3257	0.3261	0.3264
4	0.3636	0.3858	0.3948	0.3998	0.4030	0.4053	0.4068	0.4082	0.4093	0.4100	0.4113	0.4126	0.4139	0.4146	0.4152	0.4159	0.4165	0.4173	0.4180
5	0.4084	0.4358	0.4485	0.4558	0.4605	0.4635	0.4663	0.4683	0.4698	0.4711	0.4731	0.4751	0.4772	0.4782	0.4793	0.4804	0.4815	0.4827	0.4839
6	0.4356	0.4708	0.4964	0.4958	0.5017	0.5060	0.5093	0.5118	0.5139	0.5156	0.5182	0.5210	0.5238	0.5263	0.5288	0.5304	0.5320	0.5336	0.5352
7	0.4566	0.4962	0.5143	0.5231	0.5323	0.5376	0.5416	0.5447	0.5472	0.5493	0.5526	0.5560	0.5596	0.5631	0.5654	0.5674	0.5693	0.5717	0.5740
8	0.4723	0.5155	0.5357	0.5478	0.5560	0.5620	0.5666	0.5703	0.5732	0.5757	0.5785	0.5836	0.5878	0.5901	0.5924	0.5948	0.5973	0.5999	0.6025
9	0.4846	0.5306	0.5524	0.5657	0.5748	0.5815	0.5868	0.5907	0.5941	0.5968	0.6012	0.6068	0.6108	0.6133	0.6160	0.6188	0.6217	0.6247	0.6279
10	0.4943	0.5427	0.5660	0.5802	0.5901	0.5973	0.6030	0.6075	0.6111	0.6142	0.6190	0.6241	0.6297	0.6326	0.6357	0.6383	0.6421	0.6458	0.6492
12	0.5088	0.5609	0.5853	0.6022	0.6133	0.6215	0.6280	0.6331	0.6374	0.6409	0.6455	0.6502	0.6552	0.6592	0.6627	0.6664	0.6703	0.6744	0.6787
15	0.5332	0.5791	0.6099	0.6245	0.6396	0.6492	0.6555	0.6605	0.6644	0.6683	0.6732	0.6782	0.6834	0.6880	0.6915	0.6950	0.6989	0.7038	0.7082
20	0.5375	0.5972	0.6274	0.6460	0.6608	0.6713	0.6797	0.6855	0.6922	0.6971	0.7019	0.7065	0.7135	0.7203	0.7263	0.7319	0.7389	0.7464	0.7513
24	0.5445	0.6062	0.6377	0.6581	0.6728	0.6840	0.6930	0.7003	0.7064	0.7117	0.7202	0.7265	0.7335	0.7400	0.7460	0.7523	0.7591	0.7665	0.7748
30	0.5515	0.6151	0.6480	0.6684	0.6849	0.6968	0.7064	0.7143	0.7209	0.7266	0.7359	0.7432	0.7509	0.7579	0.7645	0.7715	0.7793	0.7873	0.7956
40	0.5585	0.6241	0.6582	0.6807	0.6971	0.7098	0.7203	0.7284	0.7356	0.7417	0.7518	0.7582	0.7663	0.7736	0.7807	0.7880	0.7957	0.8035	0.8117
60	0.5654	0.6329	0.6685	0.6920	0.7083	0.7227	0.7337	0.7427	0.7505	0.7571	0.7682	0.7767	0.7852	0.7937	0.8020	0.8103	0.8185	0.8268	0.8350
120	0.5722	0.6418	0.6787	0.7033	0.7216	0.7388	0.7514	0.7627	0.7698	0.7768	0.7849	0.7938	0.8026	0.8113	0.8200	0.8286	0.8372	0.8458	0.8543
∞	0.5790	0.6503	0.6886	0.7146	0.7338	0.7490	0.7614	0.7719	0.7809	0.7888	0.7950	0.8020	0.8103	0.8173	0.8251	0.8325	0.8398	0.8471	0.8543

For explanation see the panel of this table for $\beta = 0.005$.

TABLE 8.3

COMPARING TWO STANDARD DEVIATIONS

295

 $\beta = 0.995$

$\frac{\alpha_1}{\alpha_2}$	1	2	3	4	5	6	7	8	9	10	12	15	20	24	30	40	∞
1	0.00959	0.00975	0.00990	0.00994	0.00998	0.00999	0.00999	0.00999	0.00999	0.00999	0.00999	0.00999	0.00999	0.00999	0.00999	0.00999	0.00999
2	0.00326	0.00348	0.00362	0.00374	0.00382	0.00389	0.00394	0.00397	0.00399	0.00400	0.00401	0.00402	0.00403	0.00404	0.00405	0.00406	0.00407
3	0.1623	0.1618	0.1614	0.1610	0.1606	0.1602	0.1598	0.1594	0.1590	0.1586	0.1582	0.1578	0.1574	0.1570	0.1566	0.1562	0.1558
4	0.2460	0.2642	0.2717	0.2759	0.2786	0.2805	0.2819	0.2829	0.2838	0.2845	0.2855	0.2866	0.2877	0.2883	0.2889	0.2894	0.2900
5	0.2900	0.3159	0.3273	0.3338	0.3380	0.3411	0.3434	0.3451	0.3465	0.3477	0.3485	0.3493	0.3503	0.3513	0.3522	0.3532	0.3542
6	0.3213	0.3536	0.3683	0.3760	0.3827	0.3880	0.3900	0.3925	0.3945	0.3961	0.3988	0.4013	0.4040	0.4065	0.4089	0.4084	0.4100
7	0.3444	0.3819	0.3994	0.4100	0.4171	0.4223	0.4262	0.4293	0.4319	0.4339	0.4372	0.4406	0.4442	0.4461	0.4480	0.4500	0.4521
8	0.3620	0.4038	0.4237	0.4356	0.4442	0.4503	0.4550	0.4587	0.4617	0.4642	0.4681	0.4723	0.4767	0.4790	0.4814	0.4839	0.4865
9	0.3750	0.4211	0.4431	0.4567	0.4660	0.4729	0.4782	0.4825	0.4859	0.4889	0.4934	0.4983	0.5035	0.5083	0.5121	0.5152	0.5183
10	0.3871	0.4352	0.4589	0.4737	0.4839	0.4916	0.4973	0.5022	0.5061	0.5094	0.5145	0.5200	0.5259	0.5301	0.5324	0.5358	0.5394
12	0.4039	0.4566	0.4830	0.4998	0.5116	0.5204	0.5274	0.5329	0.5376	0.5414	0.5476	0.5543	0.5615	0.5685	0.5737	0.5783	0.5831
15	0.4207	0.4782	0.5018	0.5206	0.5401	0.5503	0.5584	0.5650	0.5704	0.5750	0.5825	0.5906	0.5985	0.6043	0.6094	0.6149	0.6207
20	0.4370	0.4998	0.5226	0.5420	0.5633	0.5812	0.5966	0.6083	0.6165	0.6225	0.6284	0.6344	0.6403	0.6463	0.6528	0.6599	0.6675
24	0.4400	0.5109	0.5452	0.5678	0.5942	0.6109	0.6271	0.6408	0.6509	0.6582	0.6652	0.6724	0.6797	0.6871	0.6942	0.7009	0.7079
30	0.4544	0.5215	0.5578	0.5817	0.6093	0.6260	0.6429	0.6580	0.6697	0.6773	0.6843	0.6914	0.6981	0.7051	0.7105	0.7169	0.7231
40	0.4627	0.5327	0.5705	0.5958	0.6245	0.6455	0.6653	0.6809	0.6932	0.7025	0.7104	0.7186	0.7264	0.7339	0.7407	0.7480	0.7519
60	0.4710	0.5436	0.5832	0.6100	0.6399	0.6655	0.6875	0.7059	0.7182	0.7282	0.7368	0.7444	0.7522	0.7593	0.7659	0.7719	0.7780
120	0.4793	0.5545	0.5960	0.6242	0.6544	0.6821	0.7059	0.7253	0.7381	0.7482	0.7568	0.7644	0.7722	0.7793	0.7859	0.7920	0.7980
∞	0.4875	0.5654	0.6087	0.6384	0.6698	0.6989	0.7253	0.7482	0.7668	0.7793	0.7883	0.7963	0.8035	0.8100	0.8155	0.8200	0.8258

For explanation see the preface of this table for $\beta = 0.005$.

Since, under the circumstances assumed, the assignment of the designations I and II to the products is arbitrary, it is natural to require that (26) be the reciprocal of (25). For this to be the case, it is necessary that

$$F_{0.50}^2(n_1, n_2) = F_{\beta}(n_1, n_2) \cdot F_{1-\beta}(n_1, n_2) = \frac{F_{\beta}(n_1, n_2)}{F_{\beta}(n_2, n_1)} \quad (27)$$

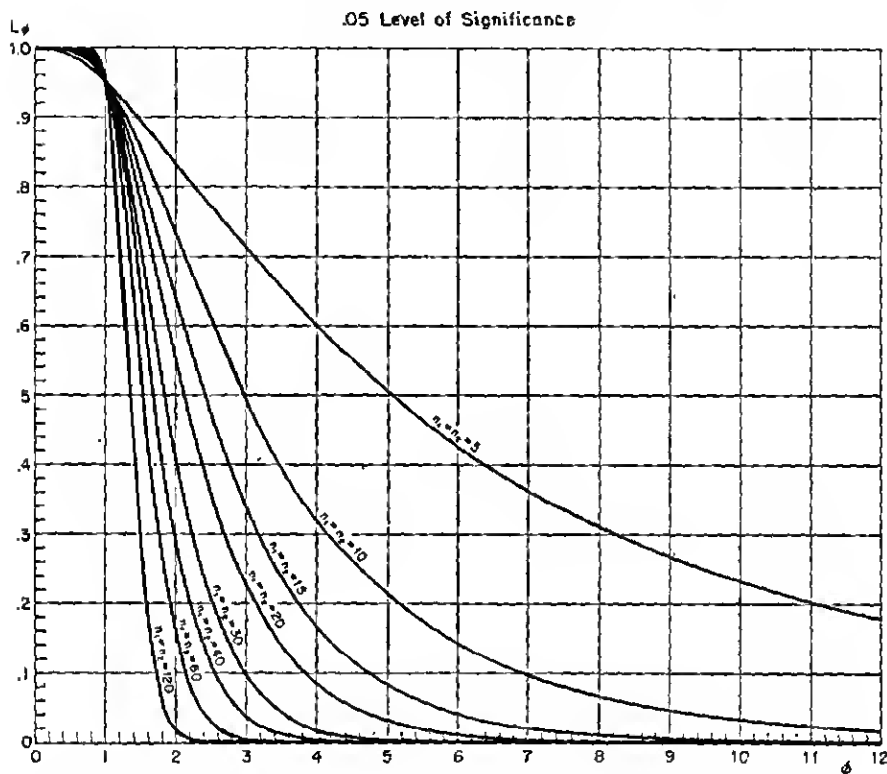


FIG. 8.3.—Operating-characteristic curves for experiments to determine whether a particular one of two new products (processes) is more variable than the other, 0.05 level of significance.

It is clear that when $n_1 = n_2$, equation (27) holds for every value of β ; it is believed that the condition $n_1 = n_2$ is necessary for the equality to hold. Consequently, if symmetry of action is considered desirable in the situation considered in this section, the test should be carried out with the same number of degrees of freedom for s_1^2 and s_2^2 .

Values of

$$\phi(0.50, \beta, n, n) = F_{\beta}(n, n) = \phi(\beta, 0.50, n, n) \quad (28)$$

can be obtained from Tables 8.3 and 8.4 by means of (27). For example, $\phi(0.50, 0.05, 30, 30) = \phi(0.05, 0.50, 30, 30) = 1.841$, from Table 8.3.

5. EXPERIMENTS INVOLVING THE ANALYSIS OF VARIANCE

5.1. Systematic and Random Variation

Many experiments are analyzed by a technique (due to R. A. Fisher) known as the analysis of variance.* Tables 8.3 and 8.4 are useful in

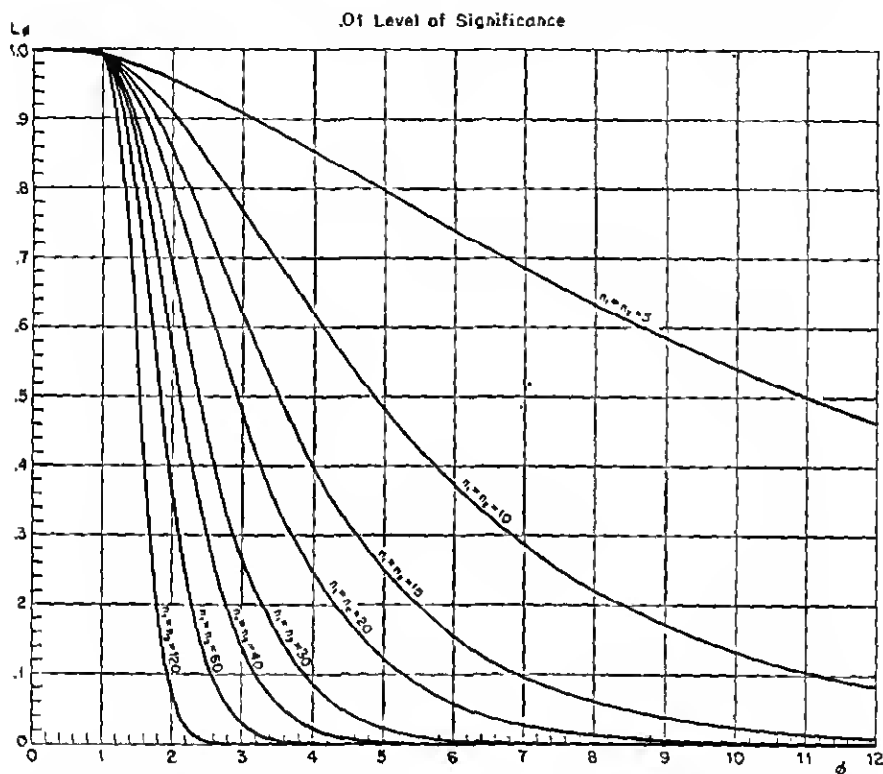


FIG. 8.4.—Operating-characteristic curves for experiments to determine whether a particular one of two new products (processes) is more variable than the other, 0.01 level of significance.

planning a certain class of such experiments, namely, those for detecting and measuring components of random variation.

The factors associated with the variation of a product can be divided into two categories:

(1) There are factors that introduce *random* variation. Lack of perfect control at some stage of a production process often acts in this

* Excellent accounts of the analysis of variance, which are especially pertinent to this chapter, are given by Baines, *Economical Design*, and Daniels, "Components of Variance."

TABLE 8.4
VALUES OF $\phi(0.01, \beta, n_1, n_2)$ CORRESPONDING TO SELECTED VALUES OF β , n_1 , AND n_2
 $\beta = 0.005$

$n_2 \backslash n_1$	1	2	3	4	5	6	7	8	9	10	12	15	20	24	30	40	60	120	∞
1	65690000	902400	300200	176200	131300	100200	96250	87860	81900	77670	7170	66190	61740	59550	57470	55500	53630	51850	50160
2	1970000	18700	4938	2609	1819	1445	1232	1057	1005	937 0	846 0	765 7	694 8	642 5	632 1	603 4	576 5	551 1	527 2
3	7370000	6138	1398	696 5	466 6	360 5	301 1	253 8	238 4	220 0	195 5	174 0	155 3	146 8	139 9	131 4	124 4	117 9	111 8
4	4770000	3596	771 2	309 9	241 5	182 9	150 5	130 3	116 6	108 8	93 73	82 39	72 54	68 11	63 98	60 12	56 52	53 10	50 02
5	3748000	2646	547 4	255 8	193 8	122 3	99 50	85 42	75 89	69 07	60 03	52 23	45 49	42 46	39 65	37 03	34 60	32 33	30 22
6	3221000	2178	438 5	201 0	120 9	93 75	75 62	64 42	56 90	51 53	44 43	38 33	33 07	30 73	28 55	26 52	24 64	22 89	21 27
7	2904000	1863	375 5	169 7	105 9	77 57	62 13	52 63	46 26	41 72	35 24	30 61	26 20	24 24	22 42	20 73	19 17	17 71	16 37
8	2694000	1724	335 0	149 6	92 56	67 31	53 61	45 19	39 56	35 56	30 29	26 78	23 62	20 20	18 61	17 14	15 77	14 51	13 33
9	2544000	1599	306 8	135 8	83 42	60 29	47 79	40 12	35 00	31 37	26 59	22 51	19 02	17 47	16 04	14 71	13 49	12 35	11 30
10	2433000	1507	286 2	125 7	76 76	55 20	43 86	36 46	31 72	28 35	23 93	20 16	16 65	15 52	14 20	12 95	11 85	10 81	9 846
12	2270000	1381	268 3	112 1	67 78	48 37	37 93	31 56	27 32	24 32	20 39	17 04	14 19	12 93	11 76	10 69	9 694	8 775	7 926
15	2139000	1268	233 4	100 0	59 89	42 38	33 00	27 29	23 50	20 82	17 31	14 33	11 81	10 69	9 661	8 710	7 853	7 023	6 273
20	201000	1167	211 2	89 35	62 94	37 12	28 68	23 55	20 16	17 76	14 64	11 99	9 747	8 757	7 834	7 002	6 225	5 507	4 842
24	1951000	1120	201 1	84 49	49 78	34 74	26 73	21 87	18 65	16 39	13 43	10 94	8 822	7 889	7 029	6 206	5 504	4 825	4 197
30	1894000	1075	191 5	79 92	46 81	32 51	24 90	20 29	17 25	15 11	12 31	9 955	7 961	7 081	6 270	5 522	4 830	4 187	3 589
40	1839000	1033	182 5	75 62	44 03	30 41	23 19	18 82	15 94	13 91	11 27	9 040	7 158	6 327	5 562	4 864	4 198	3 587	3 012
60	1787000	992 9	173 9	71 56	41 41	28 45	21 58	17 44	14 71	12 79	10 29	8 187	6 408	5 624	4 899	4 268	3 608	3 016	2 453
120	1737000	954 9	165 8	67 74	38 65	26 61	20 08	16 15	13 56	11 74	9 380	7 390	5 709	4 965	4 277	3 638	3 037	2 461	1 893
∞	1690000	918 8	158 2	64 15	36 04	24 88	18 68	14 84	12 49	10 77	8 529	6 646	5 053	4 347	3 691	3 076	2 487	1 896	1 000

Explanation

Let (a) s^2 be an estimate of σ^2 such that $\frac{n_1 s^2}{\sigma^2}$ is distributed as χ^2 for n_1 degrees of freedom

(b) s_2^2 be an estimate of σ^2 such that $\frac{n_2 s_2^2}{\sigma^2}$ is distributed independently as χ^2 for n_2 degrees of freedom

(c) $F_0(n_1, n_2)$ be the value of the variance ratio for n_1 and n_2 degrees of freedom exceeded with probability ϵ

(d) the decision $\frac{\sigma_1^2}{\sigma_2^2} > 1$, or the decision $\frac{\sigma_1^2}{\sigma_2^2} \leq 1$, be made according as $\frac{s_1^2}{s_2^2}$ exceeds or does not exceed $F_0(n_1, n_2)$

Then the probability is β that the decision $\frac{\sigma_1^2}{\sigma_2^2} \leq 1$ will be made when $\frac{\sigma_1^2}{\sigma_2^2} = \phi(0.01, \beta, n_1, n_2) = F_{1-\beta}(n_1, n_2) = F_{\epsilon}(n_1, n_2) = F_0(n_1, n_2)$.

TABLE 8.4

COMPARING TWO STANDARD DEVIATIONS

299

 $\beta = 0.01$

$\frac{n_1}{n_2}$	1	2	3	4	5	6	7	8	9	10	12	15	20	24	30	40	60	120	∞
1	16420000	492500	184300	119200	93710	80530	72908	67350	63630	60329	56979	53409	50270	49770	47350	45980	44680	43430	42240
2	482500	9801	3056	1786	1318	1065	848	685	567	481	408	342	281	235	195	161	131	103	82
3	184300	3056	807	479	340	273	233	208	184	161	141	125	108	94	81	70	61	53	46
4	119200	1780	479	255	176	130	117	103	94	87	77	69	62	56	50	45	40	35	30
5	93710	1318	340	176	120	93	78	68	61	56	50	44	39	34	30	26	22	19	16
6	80530	1065	273	139	93	71	60	51	46	42	37	32	28	24	21	18	15	13	11
7	72908	948	233	117	78	60	48	42	37	34	30	26	22	19	16	14	12	10	8
8	67350	859	208	103	68	51	42	36	32	29	25	22	19	17	15	13	11	9	7
9	63630	797	191	94	61	46	37	32	28	25	22	19	16	14	12	10	8	6	5
10	60329	751	178	87	56	42	34	29	25	22	19	16	14	12	10	8	6	5	4
12	56979	688	161	77	50	37	30	25	22	20	17	14	12	10	8	6	5	4	3
15	53409	632	145	69	44	32	26	22	19	17	14	12	10	8	6	5	4	3	2
20	50270	581	131	62	39	28	22	19	16	14	12	10	8	6	5	4	3	2	1
24	48770	536	125	58	36	26	21	17	15	13	11	9	8	7	6	5	4	3	2
30	47350	506	119	55	34	25	20	16	14	12	10	8	7	6	5	4	3	2	1
40	45980	516	113	52	32	23	18	15	13	11	9	8	7	6	5	4	3	2	1
60	44680	496	108	49	30	22	17	14	12	10	8	7	6	5	4	3	2	1	0
120	43430	476	103	47	28	20	16	13	11	9	8	7	6	5	4	3	2	1	0
∞	42240	458	98	44	27	19	14	12	10	8	7	6	5	4	3	2	1	0	0

For explanation see the panel of this table for $\beta = 0.05$.

TABLE 8.4.— $\phi(0.01, \beta, n_1, n_2)$.—(Continued)
 $\beta = 0.025$

$n_1 \backslash n_2$	1	2	3	4	5	6	7	8	9	10	12	15	20	24	30	40	60	120	∞
1	2625000	1925000	94250	68720	57080	51640	47660	45290	43420	42010	40020	38170	36450	35040	34500	34100	33370	32600	31890
2	78750	3861	1591	1057	837	721	649	602	563	542	509	473	443	429	416	403	380	375	367
3	29460	1207	454	286	219	184	163	148	138	131	121	111	103	98	95	91	87	84	81
4	19070	706	252	153	114	94	82	74	69	65	59	54	49	47	44	42	41	38	37
5	14960	521	179	106	78	63	55	49	45	42	38	34	31	29	28	26	25	24	23
6	12880	429	144	84	61	49	42	37	34	32	28	25	23	21	20	19	18	17	16
7	11610	375	123	71	51	40	34	30	28	26	23	20	18	17	16	15	14	13	12
8	10770	340	110	62	44	35	30	27	24	22	19	17	15	14	13	12	11	10	9
9	10170	315	101	57	40	32	27	24	21	19	17	15	13	12	11	10	9	8	7
10	9729	297	94	53	37	29	24	21	19	18	15	13	12	11	10	9	8	7	6
12	9113	273	85	47	33	25	21	18	16	15	13	11	10	9	8	7	6	5	4
15	8552	250	77	42	29	22	18	16	14	13	11	10	8	7	6	5	4	3	2
20	8040	230	69	37	25	20	16	14	12	11	9	8	7	6	5	4	3	2	1
24	7801	221	66	35	24	18	15	13	11	10	9	7	6	5	4	3	2	1	0
30	7573	213	63	34	23	17	14	12	10	9	8	6	5	4	3	2	1	0	0
40	7355	204	60	32	21	16	13	11	10	9	7	6	5	4	3	2	1	0	0
60	7145	196	57	30	20	15	12	10	9	8	6	5	4	3	2	1	0	0	0
120	6947	189	55	28	19	14	11	9	8	7	6	5	4	3	2	1	0	0	0
∞	6756	181	52	27	18	13	10	9	8	7	6	5	4	3	2	1	0	0	0

For explanation see the panel of this table for $\beta = 0.005$.

TABLE 8.4

COMPARING TWO STANDARD DEVIATIONS

301

 $\beta = 0.05$

$\frac{r_1}{n_1}$	1	2	3	4	5	6	7	8	9	10	12	15	20	24	30	40	60	120	∞
1	654200	92680	54720	43360	38080	33680	33180	31840	30820	30060	28990	27970	27020	26560	26110	25680	25200	24850	24450
2	19650	1881	947 2	689 2	574 6	510 9	470 7	443 1	423 0	407 8	386 3	366 1	347 4	338 4	329 8	321 5	313 4	305 6	298 1
3	7350	500 6	273 3	180 2	152 7	132 8	120 3	111 8	105 6	101 0	94 42	88 34	82 70	80 03	77 46	74 97	72 58	70 28	68 05
4	4761	346 4	182 2	102 1	80 59	68 94	61 71	56 80	53 26	50 53	46 85	43 38	40 18	38 67	37 22	35 82	34 47	33 18	31 93
5	3742	258 1	108 7	71 27	55 39	43 82	41 63	38 50	35 37	33 43	30 71	28 21	25 90	24 81	23 78	22 76	21 79	20 87	19 97
6	3216	211 2	87 43	58 38	43 26	35 27	31 93	29 01	26 91	25 33	23 12	21 09	19 22	18 34	17 50	16 69	15 91	15 16	14 44
7	2899	184 8	75 11	47 82	36 38	30 25	26 48	23 04	22 12	20 76	18 85	17 09	15 47	14 72	13 99	13 29	12 62	11 97	11 35
8	2690	167 5	67 14	42 32	31 95	26 42	23 02	20 73	19 69	17 89	16 14	14 68	13 11	12 43	11 78	11 15	10 55	9 973	9 418
9	2540	155 5	61 61	38 52	28 91	23 78	20 64	18 62	17 61	15 83	14 29	12 84	11 50	10 98	10 28	9 700	9 140	8 614	8 103
10	2420	146 6	57 57	35 75	26 68	21 67	18 91	16 93	15 51	14 44	12 90	11 59	10 34	9 756	9 193	8 682	8 134	7 635	7 156
12	2276	134 5	52 05	31 99	23 69	19 28	16 68	14 78	13 48	12 31	11 16	9 925	8 788	8 254	7 742	7 251	6 779	6 325	5 889
15	2136	123 5	47 14	28 66	21 04	17 01	14 64	12 83	11 71	10 82	9 594	8 468	7 429	6 943	6 476	6 027	5 596	5 181	4 780
20	2008	113 7	42 77	25 71	18 70	15 00	12 74	11 23	10 15	9 343	8 219	7 187	6 240	5 785	5 367	4 955	4 558	4 175	3 802
24	1948	109 2	40 76	24 36	17 63	14 09	11 92	10 43	9 444	8 672	7 596	6 609	5 702	5 275	4 864	4 468	4 086	3 715	3 354
30	1891	104 9	38 88	23 09	16 63	13 23	11 16	9 770	8 782	8 042	7 012	6 067	5 197	4 737	4 392	4 011	3 641	3 281	2 927
40	1837	100 8	37 06	21 89	15 68	12 42	10 43	9 107	8 169	7 452	6 465	5 558	4 723	4 329	3 949	3 579	3 220	2 867	2 518
60	1785	98 98	35 37	20 78	14 90	11 66	9 758	8 495	7 577	6 898	5 951	5 081	4 278	3 897	3 529	3 170	2 817	2 467	2 110
120	1735	93 27	33 76	19 69	13 96	10 95	9 122	7 801	7 000	6 378	5 469	4 633	3 858	3 490	3 131	2 779	2 429	2 072	1 666
∞	1687	89 78	32 24	18 68	13 17	10 28	8 524	7 352	6 516	5 899	5 017	4 211	3 462	3 104	2 752	2 403	2 048	1 661	1 000

For explanation see the panel of this table for $\beta = 0.005$.

TABLE 8.4.— $-\phi(0.01, \beta, n, n_2)$.—(Continued)
 $\beta = 0.10$

$n_2 \backslash n$	1	2	3	4	5	6	7	8	9	10	12	15	20	24	30	40	60	120	∞
1	161500	42630.	22630.	25560.	23400.	22120	21280	20880	20240	19890	19400.	18020	18470	18350	18040	17830.	17620	17420	17220
2	4376	891.0	541.7	429.2	375.3	344.0	323.6	309.4	298.8	290.7	279.0	268.0	257.5	252.5	247.5	242.8	238.1	233.6	229.1
3	1828	282.3	168.8	120.3	102.2	81.79	85.07	80.97	76.92	74.27	70.48	66.91	63.52	61.90	60.33	58.79	57.30	55.85	54.44
4	1184.	166.4	89.19	65.62	54.64	48.37	44.34	41.53	39.47	37.90	35.65	33.53	31.53	30.57	29.84	28.74	27.86	27.01	26.13
5	830.0	123.4	64.03	46.14	37.87	33.16	30.15	28.05	26.52	25.34	23.67	22.10	20.62	19.91	19.22	18.65	17.90	17.28	16.66
6	800.0	101.9	51.68	36.68	29.78	25.86	23.35	21.62	20.35	19.38	17.69	16.09	15.47	14.88	14.31	13.76	13.23	12.71	12.21
7	721.4	89.25	44.51	31.22	25.13	21.08	19.47	17.95	16.80	15.98	14.77	13.63	12.56	12.04	11.55	11.06	10.60	10.14	9.698
8	669.2	81.01	39.87	27.71	22.15	19.00	17.00	15.61	14.60	13.82	12.72	11.68	10.71	10.25	9.794	9.356	8.930	8.517	8.115
9	632.2	75.25	36.64	25.28	20.09	17.16	15.29	14.00	13.06	12.34	11.31	10.35	9.447	9.015	8.565	8.188	7.792	7.407	7.033
10	604.6	70.99	34.27	23.50	18.59	15.32	14.05	12.83	11.94	11.26	10.30	9.387	8.532	8.124	7.727	7.342	6.988	6.604	6.249
12	566.4	65.17	31.05	21.66	16.55	14.00	12.38	11.26	10.44	9.813	8.923	8.038	7.302	6.925	6.566	6.205	5.860	5.523	5.195
15	531.6	59.93	28.17	18.63	14.75	12.40	10.90	9.988	9.112	8.536	7.717	6.946	6.221	5.874	5.536	5.206	4.886	4.572	4.266
20	499.8	55.22	25.60	17.65	13.16	10.98	9.597	8.642	7.945	7.412	6.585	5.942	5.270	4.947	4.633	4.326	4.025	3.730	3.440
24	455.0	50.05	24.47	16.16	12.43	10.23	9.050	8.085	7.413	6.901	6.172	5.456	4.837	4.520	4.221	3.923	3.631	3.343	3.058
30	470.9	50.98	23.31	15.34	11.74	9.726	8.445	7.500	6.914	6.421	5.719	5.057	4.430	4.128	3.833	3.543	3.253	2.975	2.692
40	457.3	49.02	22.25	14.59	11.09	9.133	7.919	7.038	6.445	5.970	5.293	4.633	4.047	3.754	3.468	3.183	2.902	2.622	2.337
60	444.4	47.15	21.25	13.83	10.48	8.614	7.424	6.604	6.004	5.546	4.892	4.274	3.685	3.400	3.119	2.840	2.562	2.279	1.985
120	432.0	45.39	20.31	13.14	9.910	8.106	6.959	6.168	5.559	5.146	4.514	3.916	3.343	3.054	2.785	2.512	2.231	1.939	1.613
∞	420.2	43.71	19.41	12.48	9.369	7.628	6.521	5.757	5.198	4.770	4.159	3.578	3.019	2.745	2.471	2.192	1.902	1.580	1.000

For explanation see the part of this table for $\beta = 0.005$

TABLE 8.4

COMPARING TWO STANDARD DEVIATIONS

303

 $\beta = 0.25$

$\frac{r_1}{r_2}$	1	2	3	4	5	6	7	8	9	10	12	15	20	24	30	40	60	∞	
1	23620.	12860.	10640.	10170.	9755	9500	9336	9202	9107.	9032	8923	8818.	8715	8665	8615	8566	8518	8471	8424.
2	738.8	297.0	226.1	198.5	184.0	175.0	169.0	164.7	161.4	158.6	155.0	151.4	147.9	146.2	144.5	142.8	141.1	139.5	137.9
3	279.7	97.18	69.39	58.76	53.21	49.80	47.51	45.86	44.61	43.64	42.52	40.85	39.52	38.87	38.24	37.61	36.96	36.38	35.78
4	181.9	56.18	39.90	32.96	29.38	27.18	25.69	24.63	23.83	23.20	22.28	21.40	20.54	20.12	19.71	19.30	18.91	18.51	18.12
5	143.4	43.54	29.08	23.61	20.75	19.05	17.89	17.05	16.43	15.93	15.22	14.62	13.85	13.52	13.20	12.88	12.57	12.26	11.95
6	123.5	36.18	23.68	19.00	16.57	15.09	14.09	13.37	12.83	12.41	11.80	11.20	10.62	10.34	10.06	9.790	9.520	9.253	8.991
7	111.5	31.64	20.54	16.31	14.13	12.73	11.90	11.25	10.76	10.39	9.831	9.293	8.773	8.517	8.266	8.019	7.774	7.532	7.294
8	103.5	29.00	18.49	14.53	12.55	11.31	10.48	9.835	9.434	9.083	8.568	8.069	7.585	7.348	7.114	6.883	6.655	6.429	6.207
9	97.83	27.00	17.07	13.37	11.45	10.29	9.503	8.939	8.513	8.181	7.695	7.223	6.764	6.539	6.317	6.093	5.861	5.637	5.455
10	93.61	25.33	16.02	12.48	10.66	9.537	8.787	8.247	7.840	7.523	7.057	6.605	6.165	5.949	5.736	5.520	5.317	5.110	4.905
12	87.76	23.50	14.58	11.27	9.560	8.517	7.814	7.309	6.927	6.620	6.192	5.767	5.353	5.149	4.948	4.748	4.550	4.353	4.158
15	82.43	21.98	13.30	10.19	8.598	7.600	6.950	6.475	6.117	5.836	5.425	5.024	4.624	4.439	4.247	4.056	3.867	3.678	3.489
20	77.57	20.04	12.15	9.228	7.721	6.802	6.181	5.734	5.396	5.131	4.743	4.362	3.989	3.805	3.621	3.438	3.255	3.070	2.885
24	75.30	19.28	11.62	8.780	7.324	6.431	5.829	5.395	5.066	4.809	4.430	4.059	3.686	3.514	3.333	3.153	2.971	2.788	2.601
30	73.13	18.50	11.12	8.367	6.948	6.082	5.497	5.075	4.755	4.504	4.135	3.773	3.416	3.237	3.060	2.881	2.700	2.516	2.327
40	71.05	17.87	10.64	7.971	6.593	5.782	5.183	4.772	4.461	4.216	3.856	3.502	3.151	2.975	2.799	2.621	2.440	2.253	2.068
60	69.07	17.22	10.19	7.596	6.258	5.450	4.857	4.457	4.144	3.945	3.593	3.243	2.900	2.726	2.550	2.371	2.187	1.995	1.787
120	67.17	16.60	9.763	7.242	5.940	5.145	4.607	4.217	3.921	3.698	3.349	3.002	2.660	2.487	2.311	2.129	1.940	1.734	1.496
∞	65.35	16.01	9.366	6.908	5.641	4.807	4.342	3.962	3.673	3.445	3.107	2.771	2.431	2.258	2.079	1.892	1.690	1.455	1.000

For explanation see the preface of this table for $\beta = 0.05$.

TABLE 8.4.— $\phi(0.01, \beta, n_1, n_2)$.—(Continued)
 $\beta = 0.50$

$n_1 \backslash n_2$	1	2	3	4	5	6	7	8	9	10	12	15	20	24	30	40	50	60	70	80	90	100	120	150	200	250	300	400	500	600	700	800	900	1000		
1	4052.	3333.	3181.	3086	3044	3017	2998	2985	2974	2966	2954	2942	2930	2924	2918	2913	2907.	2902	2896																	
2	147.3	99.00	87.38	82.22	79.32	77.46	76.16	75.21	74.48	73.90	73.05	72.20	71.35	70.97	70.56	70.16	69.76	69.33	68.97																	
3	58.31	34.98	29.46	27.00	25.61	24.72	24.10	23.64	23.29	23.01	22.60	22.19	21.73	21.59	21.39	21.19	20.99	20.80	20.60																	
4	38.64	21.73	17.75	15.98	14.67	14.32	13.87	13.54	13.28	13.07	12.77	12.47	12.17	12.03	11.85	11.73	11.59	11.44	11.30																	
5	30.79	16.62	13.29	11.81	10.97	10.42	10.04	9.757	9.540	9.367	9.199	8.954	8.691	8.475	8.346	8.224	8.100	7.975	7.851																	
6	28.70	14.01	11.04	9.712	8.966	8.466	8.123	7.867	7.671	7.515	7.281	7.050	6.820	6.705	6.580	6.476	6.361	6.247	6.133																	
7	24.21	12.45	9.704	8.472	7.789	7.313	6.993	6.755	6.572	6.425	6.207	5.986	5.772	5.664	5.556	5.448	5.339	5.230	5.121																	
8	22.56	11.43	8.928	7.660	6.993	6.560	6.255	6.029	5.854	5.714	5.505	5.297	5.089	4.985	4.880	4.776	4.671	4.566	4.460																	
9	21.39	10.70	8.210	7.090	6.448	6.033	5.739	5.520	5.351	5.216	5.014	4.812	4.610	4.509	4.407	4.305	4.203	4.100	3.996																	
10	20.51	10.17	7.753	6.669	6.049	5.643	5.358	5.145	4.981	4.849	4.652	4.455	4.257	4.157	4.057	3.957	3.856	3.754	3.652																	
12	19.29	9.427	7.128	6.091	5.467	5.110	4.838	4.631	4.473	4.346	4.155	3.964	3.771	3.674	3.577	3.478	3.378	3.278	3.176																	
15	18.17	8.757	6.561	5.571	5.002	4.630	4.365	4.169	4.016	3.893	3.708	3.522	3.334	3.238	3.142	3.045	2.946	2.845	2.742																	
20	17.16	8.149	6.050	5.103	4.557	4.198	3.944	3.754	3.605	3.486	3.306	3.123	2.938	2.843	2.747	2.649	2.550	2.447	2.341																	
24	16.68	7.867	5.814	4.886	4.351	3.999	3.749	3.562	3.413	3.297	3.119	2.938	2.754	2.659	2.563	2.464	2.365	2.269	2.163																	
30	16.23	7.594	5.599	4.680	4.155	3.810	3.564	3.379	3.235	3.118	2.942	2.762	2.578	2.483	2.386	2.287	2.188	2.093	1.986																	
40	15.79	7.342	5.375	4.485	3.970	3.630	3.383	3.206	3.063	2.948	2.773	2.594	2.409	2.314	2.216	2.114	2.018	1.923	1.816																	
60	15.37	7.098	5.172	4.299	3.793	3.460	3.211	3.041	2.900	2.786	2.612	2.433	2.248	2.151	2.051	1.947	1.856	1.761	1.653																	
120	14.97	6.856	4.979	4.123	3.626	3.298	3.048	2.884	2.745	2.631	2.458	2.280	2.093	1.994	1.892	1.783	1.685	1.583	1.473																	
∞	14.58	6.644	4.795	3.955	3.467	3.144	2.911	2.756	2.597	2.484	2.312	2.132	1.943	1.842	1.735	1.619	1.499	1.382	1.258																	

For explanation see the panel of this table for $\beta = 0.005$.

TABLE 8.4

COMPARING TWO STANDARD DEVIATIONS

305

 $\beta = 0.75$

$\frac{n_1}{n_2}$	1	2	3	4	5	6	7	8	9	10	12	15	20	24	30	40	60	120	∞
1	695.2	686.6	658.9	655.5	653.5	652.2	651.3	650.7	650.2	649.8	649.2	648.6	648.0	647.7	647.4	647.2	646.9	646.5	646.3
2	38.31	33.00	31.45	30.71	30.28	29.99	29.79	29.64	29.53	29.43	29.30	29.16	29.03	28.96	28.89	28.82	28.76	28.69	28.62
3	16.86	13.52	12.51	12.01	11.72	11.52	11.39	11.28	11.20	11.14	11.04	10.94	10.85	10.80	10.75	10.70	10.66	10.61	10.56
4	11.73	9.000	8.157	7.740	7.490	7.323	7.203	7.113	7.043	6.987	6.902	6.816	6.731	6.688	6.645	6.602	6.558	6.515	6.471
5	9.606	7.164	6.400	6.019	5.788	5.633	5.522	5.437	5.371	5.319	5.238	5.157	5.076	5.035	4.993	4.952	4.910	4.868	4.825
6	8.477	6.200	5.481	5.119	4.899	4.751	4.643	4.552	4.486	4.437	4.369	4.290	4.210	4.169	4.128	4.087	4.046	4.004	3.961
7	7.764	5.612	4.922	4.573	4.360	4.216	4.111	4.031	3.969	3.918	3.841	3.763	3.683	3.643	3.602	3.561	3.519	3.477	3.434
8	7.319	5.220	4.550	4.210	4.001	3.859	3.756	3.677	3.615	3.565	3.489	3.411	3.331	3.291	3.250	3.208	3.166	3.123	3.080
9	6.984	4.941	4.286	3.951	3.746	3.606	3.503	3.423	3.362	3.314	3.239	3.160	3.080	3.039	2.998	2.956	2.913	2.870	2.825
10	6.734	4.732	4.088	3.758	3.555	3.416	3.315	3.237	3.176	3.129	3.050	2.972	2.892	2.851	2.809	2.767	2.723	2.679	2.634
12	6.335	4.442	3.814	3.491	3.291	3.154	3.053	2.976	2.915	2.865	2.788	2.710	2.629	2.587	2.545	2.501	2.456	2.410	2.363
15	6.083	4.176	3.563	3.247	3.050	2.914	2.814	2.737	2.676	2.626	2.549	2.469	2.387	2.344	2.300	2.255	2.209	2.161	2.111
20	5.768	3.933	3.335	3.024	2.829	2.695	2.595	2.518	2.457	2.407	2.329	2.248	2.163	2.119	2.073	2.028	1.977	1.925	1.871
24	5.629	3.820	3.225	2.920	2.727	2.593	2.493	2.416	2.355	2.304	2.226	2.144	2.058	2.012	1.965	1.917	1.865	1.811	1.754
30	5.408	3.711	3.126	2.821	2.628	2.495	2.395	2.318	2.256	2.206	2.127	2.044	1.956	1.909	1.861	1.810	1.756	1.699	1.637
40	5.368	3.607	3.029	2.726	2.535	2.401	2.302	2.224	2.162	2.111	2.031	1.947	1.857	1.809	1.760	1.705	1.649	1.587	1.519
60	5.245	3.508	2.936	2.635	2.445	2.312	2.212	2.135	2.072	2.020	1.939	1.854	1.761	1.711	1.659	1.603	1.542	1.474	1.395
120	5.127	3.413	2.847	2.548	2.359	2.226	2.127	2.049	1.986	1.933	1.851	1.763	1.668	1.616	1.560	1.500	1.433	1.355	1.256
∞	5.014	3.322	2.762	2.465	2.277	2.144	2.044	1.966	1.902	1.849	1.768	1.676	1.577	1.523	1.462	1.396	1.319	1.222	1.000

For explanation see the panel of this table for $\beta = 0.005$.

TABLE 8.4.— $\phi(0.01, \beta, n, n_2)$.—(Continued)
 $\beta = 0.90$

n_1	1	2	3	4	5	6	7	8	9	10	12	15	20	24	30	40	60	120	∞
1	101.7	101.0	100.8	100.7	100.7	100.7	100.6	100.6	100.6	100.6	100.6	100.6	100.6	100.6	100.6	100.5	100.5	100.5	100.5
2	11.55	11.00	10.83	10.74	10.69	10.65	10.63	10.61	10.60	10.58	10.57	10.55	10.53	10.53	10.53	10.52	10.51	10.50	10.49
3	6.100	5.642	5.404	5.374	5.319	5.281	5.255	5.234	5.219	5.206	5.187	5.167	5.148	5.138	5.129	5.119	5.109	5.099	5.089
4	4.604	4.162	3.933	3.890	3.832	3.792	3.763	3.742	3.725	3.711	3.690	3.670	3.647	3.636	3.625	3.614	3.602	3.591	3.580
5	4.004	3.512	3.332	3.290	3.236	3.176	3.135	3.105	3.081	3.063	3.048	3.033	3.009	2.979	2.967	2.953	2.930	2.918	2.905
6	3.600	3.155	2.974	2.932	2.876	2.814	2.772	2.740	2.716	2.697	2.681	2.657	2.633	2.608	2.595	2.582	2.558	2.541	2.527
7	3.412	2.931	2.749	2.706	2.650	2.587	2.543	2.511	2.486	2.466	2.450	2.425	2.399	2.372	2.359	2.345	2.316	2.302	2.287
8	3.256	2.778	2.596	2.553	2.496	2.432	2.388	2.354	2.328	2.308	2.291	2.265	2.238	2.210	2.196	2.181	2.151	2.136	2.119
9	3.143	2.663	2.480	2.437	2.380	2.316	2.271	2.240	2.214	2.193	2.175	2.149	2.121	2.092	2.077	2.062	2.030	2.013	1.990
10	3.058	2.575	2.402	2.359	2.301	2.237	2.192	2.154	2.127	2.106	2.088	2.060	2.032	2.002	1.986	1.970	1.937	1.920	1.902
12	2.937	2.453	2.285	2.242	2.182	2.118	2.063	2.025	1.997	1.975	1.954	1.925	1.895	1.865	1.849	1.832	1.804	1.785	1.765
15	2.825	2.339	2.176	2.133	2.072	2.008	1.952	1.914	1.886	1.863	1.841	1.811	1.781	1.751	1.735	1.716	1.687	1.666	1.634
20	2.722	2.235	2.075	2.032	1.970	1.906	1.850	1.812	1.784	1.760	1.738	1.707	1.677	1.648	1.632	1.613	1.584	1.562	1.508
24	2.673	2.212	2.057	2.014	1.952	1.888	1.832	1.794	1.766	1.742	1.719	1.688	1.658	1.629	1.613	1.594	1.565	1.543	1.470
30	2.625	2.166	2.015	1.972	1.910	1.846	1.790	1.752	1.724	1.700	1.677	1.646	1.616	1.587	1.571	1.552	1.523	1.501	1.422
40	2.580	2.122	1.975	1.932	1.870	1.806	1.750	1.712	1.684	1.660	1.637	1.606	1.576	1.547	1.531	1.512	1.483	1.461	1.378
60	2.535	2.080	1.895	1.852	1.790	1.726	1.670	1.632	1.604	1.580	1.557	1.526	1.496	1.467	1.451	1.432	1.403	1.381	1.311
120	2.493	2.038	1.853	1.810	1.748	1.684	1.628	1.590	1.562	1.538	1.515	1.484	1.454	1.425	1.409	1.390	1.361	1.339	1.289
∞	2.452	2.000	1.815	1.772	1.710	1.646	1.590	1.552	1.524	1.500	1.477	1.446	1.416	1.387	1.371	1.352	1.323	1.301	1.000

For explanation see the panel of this table for $\beta = 0.005$

TABLE 8.4

COMPARING TWO STANDARD DEVIATIONS

307

 $\beta = 0.95$

n_1 n_2	1	2	3	4	5	6	7	8	9	10	12	15	20	24	30	40	60	120	∞
1	25.10	25.06	25.05	25.04	25.04	25.04	25.04	25.04	25.04	25.04	25.04	25.03	25.03	25.03	25.03	25.03	25.03	25.03	25.03
2	5.321	5.211	5.175	5.157	5.146	5.139	5.134	5.130	5.127	5.125	5.121	5.118	5.114	5.112	5.111	5.109	5.107	5.106	5.104
3	3.368	3.226	3.175	3.133	3.122	3.114	3.114	3.103	3.103	3.099	3.094	3.088	3.082	3.079	3.076	3.073	3.070	3.067	3.064
4	2.750	2.592	2.533	2.501	2.481	2.467	2.457	2.450	2.444	2.439	2.431	2.424	2.416	2.412	2.408	2.404	2.400	2.396	2.392
5	2.480	2.294	2.229	2.194	2.172	2.156	2.144	2.135	2.129	2.123	2.114	2.105	2.096	2.091	2.086	2.081	2.077	2.072	2.067
6	2.206	2.124	2.056	2.018	1.993	1.976	1.964	1.954	1.946	1.939	1.930	1.919	1.909	1.904	1.898	1.893	1.887	1.881	1.875
7	2.190	2.015	1.944	1.904	1.878	1.860	1.847	1.836	1.827	1.820	1.810	1.799	1.787	1.781	1.775	1.769	1.762	1.756	1.749
8	2.117	1.940	1.867	1.826	1.798	1.779	1.765	1.754	1.745	1.737	1.726	1.714	1.701	1.695	1.688	1.681	1.674	1.667	1.660
9	2.054	1.895	1.810	1.768	1.740	1.720	1.705	1.693	1.683	1.675	1.663	1.651	1.637	1.630	1.623	1.616	1.608	1.601	1.593
10	2.023	1.842	1.767	1.723	1.695	1.674	1.658	1.646	1.636	1.628	1.615	1.602	1.588	1.581	1.573	1.565	1.557	1.549	1.540
12	1.965	1.783	1.705	1.660	1.631	1.609	1.592	1.580	1.569	1.560	1.547	1.532	1.517	1.509	1.501	1.492	1.483	1.473	1.464
13	1.911	1.727	1.648	1.601	1.570	1.548	1.530	1.516	1.505	1.496	1.481	1.465	1.449	1.440	1.431	1.421	1.411	1.400	1.389
20	1.861	1.675	1.594	1.546	1.513	1.490	1.471	1.457	1.445	1.435	1.419	1.402	1.383	1.373	1.363	1.352	1.340	1.327	1.314
24	1.836	1.650	1.568	1.519	1.486	1.463	1.443	1.426	1.416	1.405	1.388	1.371	1.351	1.340	1.329	1.317	1.305	1.291	1.276
30	1.813	1.626	1.543	1.494	1.460	1.435	1.416	1.400	1.387	1.376	1.359	1.340	1.319	1.308	1.296	1.283	1.269	1.254	1.237
40	1.791	1.602	1.519	1.469	1.434	1.409	1.389	1.373	1.360	1.349	1.330	1.310	1.288	1.276	1.263	1.249	1.233	1.216	1.196
60	1.769	1.580	1.496	1.445	1.410	1.384	1.363	1.346	1.333	1.321	1.302	1.281	1.257	1.243	1.230	1.214	1.197	1.177	1.152
120	1.748	1.558	1.474	1.422	1.386	1.359	1.338	1.321	1.306	1.294	1.274	1.252	1.227	1.212	1.197	1.179	1.159	1.134	1.101
∞	1.727	1.537	1.452	1.399	1.363	1.335	1.313	1.296	1.281	1.268	1.247	1.223	1.196	1.180	1.163	1.142	1.118	1.084	1.000

For explanation see the panel of this table for $\beta = 0.05$.

TABLE S.4.— $\phi(0.01, \beta, n_1, n_2)$.—(Continued)
 $\beta \approx 0.975$

$\frac{n_1}{n_2}$	1	2	3	4	5	6	7	8	9	10	12	15	20	24	30	40	60	120	∞
1	6.245	6.253	6.253	6.252	6.252	6.252	6.252	6.252	6.252	6.253	6.252	6.252	6.252	6.252	6.252	6.252	6.252	6.252	6.252
2	2.538	2.538	2.532	2.529	2.527	2.526	2.525	2.524	2.523	2.523	2.522	2.522	2.521	2.521	2.520	2.520	2.520	2.519	2.519
3	1.986	1.921	1.908	1.901	1.897	1.894	1.892	1.891	1.889	1.888	1.887	1.885	1.884	1.883	1.882	1.882	1.881	1.880	1.879
4	1.735	1.690	1.673	1.663	1.658	1.653	1.650	1.648	1.646	1.645	1.643	1.640	1.638	1.637	1.635	1.634	1.633	1.632	1.630
5	1.625	1.574	1.553	1.542	1.535	1.529	1.526	1.523	1.520	1.518	1.516	1.513	1.509	1.508	1.506	1.505	1.503	1.501	1.500
6	1.500	1.450	1.432	1.420	1.411	1.403	1.400	1.397	1.393	1.390	1.388	1.385	1.381	1.378	1.374	1.371	1.369	1.366	1.364
7	1.517	1.459	1.435	1.421	1.412	1.403	1.400	1.396	1.391	1.387	1.384	1.381	1.377	1.373	1.368	1.364	1.360	1.357	1.354
8	1.487	1.427	1.402	1.387	1.377	1.370	1.364	1.360	1.355	1.354	1.351	1.349	1.345	1.340	1.337	1.333	1.330	1.327	1.324
9	1.465	1.404	1.377	1.361	1.351	1.343	1.337	1.333	1.329	1.326	1.321	1.316	1.311	1.308	1.306	1.303	1.300	1.297	1.293
10	1.448	1.385	1.358	1.342	1.331	1.323	1.317	1.312	1.308	1.305	1.300	1.294	1.289	1.286	1.283	1.280	1.276	1.273	1.269
12	1.424	1.359	1.330	1.313	1.302	1.293	1.286	1.281	1.277	1.273	1.268	1.262	1.256	1.252	1.249	1.245	1.241	1.237	1.233
15	1.401	1.335	1.304	1.286	1.274	1.265	1.258	1.252	1.247	1.243	1.237	1.231	1.224	1.220	1.216	1.212	1.207	1.203	1.198
20	1.379	1.311	1.280	1.261	1.247	1.238	1.230	1.224	1.219	1.214	1.208	1.200	1.193	1.188	1.183	1.178	1.173	1.167	1.161
24	1.368	1.300	1.268	1.248	1.235	1.224	1.216	1.210	1.205	1.200	1.193	1.185	1.176	1.172	1.167	1.161	1.156	1.149	1.143
30	1.358	1.289	1.256	1.236	1.222	1.212	1.203	1.197	1.191	1.186	1.179	1.170	1.161	1.156	1.150	1.145	1.138	1.131	1.123
40	1.348	1.278	1.245	1.225	1.210	1.199	1.191	1.184	1.178	1.173	1.165	1.156	1.146	1.140	1.134	1.127	1.120	1.112	1.102
60	1.339	1.268	1.234	1.213	1.198	1.187	1.178	1.171	1.165	1.159	1.151	1.141	1.130	1.124	1.118	1.110	1.102	1.092	1.080
120	1.330	1.258	1.224	1.202	1.187	1.175	1.166	1.158	1.152	1.146	1.137	1.127	1.115	1.108	1.101	1.092	1.082	1.070	1.053
∞	1.321	1.248	1.214	1.191	1.176	1.164	1.154	1.146	1.139	1.133	1.123	1.112	1.099	1.092	1.083	1.073	1.061	1.044	1.000

For explanation see the panel of this table for $\beta = 0.005$

TABLE 8.4

COMPARING TWO STANDARD DEVIATIONS

309

 $\beta = 0.995$

n_1 n_2	1	2	3	4	5	6	7	8	9	10	12	15	20	24	30	40	60	120	∞
1	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500
2	0.4962	0.4975	0.4979	0.4991	0.4993	0.4993	0.4994	0.4994	0.4995	0.4995	0.4995	0.4995	0.4996	0.4996	0.4997	0.4997	0.4997	0.4997	0.4997
3	0.6141	0.6188	0.6206	0.6215	0.6221	0.6225	0.6228	0.6230	0.6231	0.6233	0.6235	0.6237	0.6239	0.6240	0.6241	0.6243	0.6244	0.6245	0.6246
4	0.6765	0.6848	0.6892	0.6900	0.6912	0.6920	0.6926	0.6931	0.6935	0.6938	0.6942	0.6947	0.6952	0.6954	0.6957	0.6959	0.6961	0.6964	0.6967
5	0.7135	0.7243	0.7296	0.7323	0.7341	0.7353	0.7363	0.7370	0.7376	0.7381	0.7388	0.7396	0.7403	0.7407	0.7411	0.7415	0.7420	0.7424	0.7428
6	0.7376	0.7512	0.7571	0.7606	0.7629	0.7646	0.7659	0.7668	0.7676	0.7682	0.7689	0.7697	0.7702	0.7719	0.7724	0.7730	0.7736	0.7742	0.7748
7	0.7542	0.7696	0.7766	0.7808	0.7835	0.7855	0.7870	0.7882	0.7892	0.7900	0.7912	0.7923	0.7938	0.7945	0.7953	0.7960	0.7968	0.7976	0.7984
8	0.7665	0.7833	0.7910	0.7957	0.7986	0.8011	0.8029	0.8043	0.8054	0.8063	0.8078	0.8093	0.8110	0.8118	0.8127	0.8136	0.8145	0.8155	0.8165
9	0.7757	0.7937	0.8021	0.8072	0.8107	0.8133	0.8152	0.8168	0.8181	0.8191	0.8208	0.8225	0.8244	0.8254	0.8264	0.8275	0.8286	0.8298	0.8309
10	0.7831	0.8019	0.8109	0.8164	0.8201	0.8229	0.8251	0.8268	0.8282	0.8294	0.8312	0.8332	0.8353	0.8364	0.8376	0.8388	0.8400	0.8414	0.8427
12	0.7938	0.8140	0.8238	0.8298	0.8342	0.8373	0.8398	0.8418	0.8434	0.8448	0.8469	0.8492	0.8518	0.8531	0.8545	0.8560	0.8575	0.8591	0.8609
15	0.8041	0.8257	0.8365	0.8432	0.8480	0.8516	0.8544	0.8567	0.8586	0.8601	0.8627	0.8654	0.8685	0.8701	0.8718	0.8736	0.8755	0.8776	0.8798
20	0.8142	0.8372	0.8488	0.8563	0.8616	0.8657	0.8689	0.8715	0.8737	0.8755	0.8785	0.8818	0.8854	0.8875	0.8896	0.8918	0.8943	0.8970	0.8999
24	0.8190	0.8425	0.8549	0.8627	0.8683	0.8725	0.8761	0.8789	0.8812	0.8832	0.8865	0.8900	0.8941	0.8963	0.8987	0.9012	0.9041	0.9072	0.9107
30	0.8236	0.8473	0.8606	0.8687	0.8750	0.8795	0.8832	0.8862	0.8887	0.8906	0.8944	0.8984	0.9028	0.9063	0.9090	0.9109	0.9142	0.9178	0.9220
40	0.8285	0.8526	0.8667	0.8753	0.8815	0.8864	0.8903	0.8935	0.8962	0.8985	0.9024	0.9067	0.9117	0.9145	0.9175	0.9209	0.9247	0.9291	0.9342
60	0.8331	0.8579	0.8725	0.8814	0.8880	0.8931	0.8973	0.9007	0.9037	0.9062	0.9104	0.9151	0.9207	0.9238	0.9274	0.9313	0.9355	0.9412	0.9479
120	0.8376	0.8641	0.8781	0.8875	0.8944	0.8996	0.9043	0.9079	0.9111	0.9138	0.9184	0.9236	0.9298	0.9335	0.9375	0.9422	0.9478	0.9548	0.9645
∞	0.8421	0.8692	0.8837	0.8934	0.9007	0.9064	0.9111	0.9151	0.9185	0.9214	0.9264	0.9322	0.9392	0.9434	0.9482	0.9540	0.9612	0.9713	1.000

For explanation see the panel of the table for $\beta = 0.005$.

manner, and the material produced exhibits an inherent random variability. This random variation may have assignable components. For instance, the thickness of washers punched from a single sheet may be regarded as varying at random about the mean thickness of washers from that sheet, because of the inherent nonuniformity of the sheet; and washers produced during a given shift may have still greater variation about the mean thickness for the shift, because of an additional component of variation assignable to the random variation of the mean thicknesses of the respective sheets about the over-all mean thickness of the sheets on that shift, and so forth.

(2) There are factors that introduce *systematic* variation. For instance, in a production unit composed of several similar machines producing the same product simultaneously, there are generally systematic differences among the machines, which superpose a pattern of variation on the output of that production unit.

In using analysis of variance merely to determine whether the over-all variation has a component assignable to a particular factor, the computational procedure and the mechanics of the statistical test are the same in the case of a factor that may contribute a component of random variation as in the case of a factor that may contribute a component of systematic variation. On the other hand, in planning such investigations and in the estimation of the magnitude(s) of the component(s), the distinction has to be taken into account, since the situations between which discrimination is required differ in the two cases, leading to differences in the computation of probabilities of errors of the second kind. *We consider only cases where random variation alone is present.*

The question arises as to how to decide in a given case whether a component of variation is systematic or random. The answer depends upon the extent to which the experimental procedure samples the material at random. If a sampling operation is such that each item of the population has an equal chance of being included in the sample, and separate drawings are independent except for any dependence resulting from the number of items in the population being limited, then the sampling is random and the sample may be termed a random sample.* When an experimenter selects two or more treatments for comparison in some respect, he rarely, if ever, selects them at random from a population of possible treatments; he selects those he believes most promising. Accordingly, components of variation assignable to differences between treatments are systematic. On the other hand, when an experimenter

* It is important to note that it is the operation of drawing the sample that is random and not the sample itself, since any sample whatsoever can be obtained by either a *random* or a *nourandom* operation.

selects a sample of items from a production lot (or a sample of animals from a herd) for a study of the effects of the treatments, he can ensure that they are a random sample from the lot, or herd, by introducing randomization into the sampling procedure, for example, by drawing cards from a hat after thorough mixing, or by using a table of random numbers. He may consider such a sample to be a random sample from the production process (or the animal species) only by making the assumption that the lot (herd) *itself is a random sample from the process (species)*. When a particular experiment is being planned, or the results of a completed experiment are being interpreted, the following two parallel sets of questions will serve to focus attention on the issue of systematic versus random variation:

(1) Are the conclusions to be confined to the things actually studied (the sample of items, or animals), or to the immediate sources of these things (the actual machines, or lots, or herds from which the things studied were obtained); or are they to be expanded to apply to the underlying populations (real or hypothetical population of machines, or the production process, or the species)?

(2) In complete repetitions of the experiment, would the same things be studied again (the same items, animals, or treatments); would new samples be drawn from the identical sources (the same machines, the same lots, or the same herds); or would new samples be drawn from the underlying populations (samples of items from different machines, or animals from different herds of the same breed)?

5.2. A Typical Analysis of Variance

This section gives a typical analysis-of-variance table for cases in which the random deviations involved are normally distributed. The conditions are specified under which the test of significance customarily associated with this table can be regarded as a test of the hypothesis that two variances σ_1^2 and σ_2^2 are equal, relative to the alternative that $\sigma_1^2 = \sigma_2^2 + K\sigma_3^2$, where K is a known constant and σ_3^2 is an unknown variance. Under these conditions the results given in Sec. 4.1 can be used in the planning and interpretation of experiments leading to analysis of variance tests of significance.

Let x_{ij} denote the j th observation in the i th group ($i = 1, 2, \dots, k$; $j = 1, 2, \dots, n_i$), let \bar{x}_i denote the average of the n_i observations in the i th group ($i = 1, 2, \dots, k$), and let $\bar{x}_..$ denote the average of all $N = \sum_{i=1}^k n_i$ observations; then the analysis-of-variance table takes the following form:

Variation	Degrees of freedom	Sum of squares	Mean square	Expectation of mean square
Between group averages . . .	$k - 1$	$S_b^2 = \sum_{i=1}^k n_i (x_{i.} - x_{..})^2$	$S_b^2 / (k - 1) = s_b^2$	$\sigma^2 + \bar{n}\sigma_\theta^2$
Within groups . . .	$N - k$	$S_w^2 = \sum_{i=1}^k \sum_{j=1}^{n_i} (x_{ij} - x_{i.})^2$	$S_w^2 / (N - k) = s_w^2$	σ^2

$$\bar{n} = (N^2 - \sum_{i=1}^k n_i^2) / N(k - 1); \text{ when } n_1 = n_2 = \dots = n_k = n, \bar{n} = n.$$

If the x_{ij} are independently and normally distributed about the respective true means m_i of the groups with common (unknown) variance σ^2 , and if the groups are a random selection from a population of groups such that in repeated selection the m_i would be normally distributed about an over-all population mean of m with variance σ_θ^2 , the x_{ij} will be normally distributed about m with variance

$$\sigma_z^2 = \sigma^2 + \sigma_\theta^2 \quad (29)$$

likewise

$$\frac{(k - 1)s_b^2}{\sigma^2 + \bar{n}\sigma_\theta^2} \quad (30)$$

will be distributed as χ^2 for $(k - 1)$ degrees of freedom; and finally

$$\frac{(N - k)s_w^2}{\sigma^2} \quad (31)$$

will be distributed independently as χ^2 for $(N - k)$ degrees of freedom.

A comparison of (30) and (31) with the assumptions made with regard to s_1^2 and s_2^2 in Sec. 4.1 reveals that if we set

$$\sigma_1^2 = \sigma^2 + \bar{n}\sigma_\theta^2 \quad \text{and} \quad \sigma_2^2 = \sigma^2 \quad (32)$$

$$n_1 = (k - 1) \quad \text{and} \quad n_2 = N - k \quad (33)$$

s_b^2 becomes identified with s_1^2 and s_w^2 with s_2^2 , and the rule of procedure becomes

(a) Accept $\sigma_\theta^2 = 0$ (there exists no between-group component of random variation) whenever

$$\frac{s_b^2}{s_w^2} \leq F_\alpha(k - 1, N - k) \quad (34)$$

(b) Accept $\sigma_g^2 > 0$ (there exists a between-group component of random variation) whenever

$$\frac{s_b^2}{s_w^2} > F_\alpha(k-1, N-k) \quad (35)$$

Since σ_g^2 cannot be negative, the probability of an error of the first kind (concluding that $\sigma_g^2 > 0$ when actually $\sigma_g^2 = 0$) is exactly α , and the probability of an error of the second kind (concluding that $\sigma_g^2 = 0$ when actually $\sigma_g^2 > 0$) is β when

$$1 + \bar{n} \left(\frac{\sigma_g^2}{\sigma^2} \right) = \phi(\alpha, \beta, k-1, N-k) \quad (36)$$

If there are n observations in each group; $\bar{n} = n$ and

$$N - k = k(n-1);$$

so*

$$\frac{\sigma_g^2}{\sigma^2} = \frac{\phi(\alpha, \beta, k-1, k(n-1)) - 1}{n} \quad (37)$$

5.3. Illustrations

The following examples illustrate types of questions to which answers may be obtained with the aid of (37):

Example VII. It is suspected that differences between lots contribute to the random variation of a particular characteristic of a certain product. To investigate this hypothesis, n items are to be selected at random and measured, from each of k lots chosen at random from the lots currently accessible. It is agreed that the test of significance defined by (34) and (35) is to be conducted at the 0.05 level of significance, and it is desired to have a probability not greater than 0.50 of falsely concluding $\sigma_g^2 = 0$ if $\sigma_g^2/\sigma^2 = 0.10$. What combination of values of k and n will accomplish this with a minimum total number of measurements?

Baines has prepared the following table for answering such questions when $\alpha = 0.05$ and $\beta = 0.50$:

k	2	3	4	5	6	7	8	9	10	14	17	21	27
n	75	34	24	19	16	14	13	12	11	9	8	7	6
kn	150	102	96	95	96	98	104	108	110	126	136	147	162
σ_g^2/σ^2	0.101	0.101	0.100	0.100	0.103	0.104	0.101	0.100	0.102	0.099	0.099	0.100	0.102

It is seen that the best combination is 19 items from each of 5 lots, requiring a total of 95 measurements. However, if it is more con-

* BAINES, *Economical Design*, tabulates (37) for $\alpha = 0.05$, $\beta = 0.50$, $k = 2$ to 31 by steps of 1, and $n = 1$ to 31 by steps of 1, 31 to 45 by steps of 2, 45 to 93 by steps of 4, 101, and 121.

venient to use 4 lots than 5 lots, 24 items from each of 4 lots will be equally effective and will require only one additional measurement.

Example VIII. If it were agreed initially in planning a test of the type discussed in Example VII that a total of 96 measurements would be employed, then the problem would arise of determining the combination of values of k and n , subject to the restriction $kn = 96$, that minimizes the value of σ_0^2/σ^2 for a given β .

Baines gives the figures tabulated below, which apply when $\alpha = 0.05$ and $\beta = 0.50$:

k	2	3	4	6	8	12	16	24
n	48	32	24	16	12	8	6	4
σ_0^2/σ^2	0.158	0.107	0.100	0.103	0.110	0.126	0.143	0.178

It is clear that the combination $k = 4$, $n = 24$ provides the most stringent test having $\alpha = 0.05$ and $kn = 96$, in the sense that it yields the minimum indifference point.

In order to answer readily questions of the type illustrated by Examples VII and VIII when α and β differ from 0.05 and 0.50, respectively, tables of (37) should be prepared using k and n as arguments. Indeed, to facilitate the planning of experiments leading to analysis-of-variance tests corresponding to two-way classifications ("rows" and "columns"), to Latin square designs, and so forth, sets of such tables will have to be prepared for each type of design, since the number of degrees of freedom corresponding to the estimate of error variance s_2^2 depends upon the design of the experiment [for a two-way classification, for example, $n_2 = (r - 1)(c - 1)$], as does also the number of degrees of freedom corresponding to the estimate of variance s_1^2 to be tested. Until such tables are available, these questions can be answered, with considerable effort expended on interpolation, by means of Tables 8.3 and 8.4. Furthermore, Tables 8.3 and 8.4 will often suffice to determine a few points on the operating-characteristic curve of a test of significance corresponding to an experimental design already agreed upon.

6. TECHNICAL NOTES

6.1. Method of Construction and Accuracy of Tables 8.1 and 8.2

As explained in Sec. 2, the standard procedure for determining whether a new product or process is more variable than a standard product or process is to compute the statistic s_1^2/σ_0^2 and

(a) Accept the conclusion $\sigma_1^2/\sigma_0^2 \leq 1$ whenever

$$\frac{s_1^2}{\sigma_1^2} \leq \frac{\chi_\alpha^2(n_1)}{n_1} \quad (38)$$

(b) Accept the conclusion $\sigma_1^2/\sigma_0^2 > 1$ whenever

$$\frac{s_1^2}{\sigma_0^2} > \frac{\chi_\alpha^2(n_1)}{n_1} \quad (39)$$

where $\chi_\alpha^2(n_1)$ is the α level of significance of χ^2 for n_1 degrees of freedom. The level of significance α represents the probability of accepting the conclusion $\sigma_1^2/\sigma_0^2 > 1$ when in fact $\sigma_1^2/\sigma_0^2 = 1$ (error of the first kind). Using this level of significance, the probability of accepting the conclusion $\sigma_1^2/\sigma_0^2 \leq 1$ when in fact $\sigma_1^2/\sigma_0^2 > 1$ (error of the second kind) depends on the ratio $\rho = \sigma_1^2/\sigma_0^2$ and is exactly β if ρ has the value

$$\rho(\alpha, \beta, n_1) = \frac{\chi_\alpha^2(n_1)}{\chi_{1-\beta}^2(n_1)} \quad (40)$$

The proof is elementary. Since the conclusion $\sigma_1^2/\sigma_0^2 \leq 1$ will be reached whenever (38) occurs, the probability of this conclusion, given $\sigma_1^2 = \rho\sigma_0^2$, is

$$\begin{aligned} P \left\{ \frac{s_1^2}{\sigma_0^2} \leq \frac{\chi_\alpha^2(n_1)}{n_1} \middle| \sigma_1^2 = \rho\sigma_0^2 \right\} &= P \left\{ \frac{n_1 s_1^2}{\sigma_1^2} \leq \frac{\sigma_0^2}{\sigma_1^2} \chi_\alpha^2(n_1) \middle| \sigma_1^2 = \rho\sigma_0^2 \right\} \\ &= P \left\{ \chi^2(n_1) \leq \frac{\chi_\alpha^2(n_1)}{\rho} \right\} \\ &= 1 - P \left\{ \chi^2(n_1) > \frac{\chi_\alpha^2(n_1)}{\rho} \right\} \end{aligned} \quad (41)$$

From (40),

$$\frac{\chi_\alpha^2(n_1)}{\rho} = \chi_{1-\beta}^2(n_1) \quad (42)$$

so the last form of (41) becomes

$$1 - (1 - \beta) = \beta \quad (43)$$

which completes the proof.*

Thompson's table of $\chi_\alpha^2(n_1)$ was used in constructing Tables 8.1 and 8.2. Direct substitution of these values in formula (40) yields values of $\rho(\alpha, \beta, n)$ corresponding to $\alpha = 0.05$ and 0.01 and to $\beta = 0.005, 0.01, 0.025, 0.05, 0.10, 0.25, 0.50, 0.750, 0.900, 0.950, 0.975, 0.990$, and 0.995 for $n = 1$ to 30 by steps of 1 and 30 to 100 by steps of 10 . The values of $\rho(0.05, \beta, n)$, rounded to 5 figures or 4 decimals, are given in

* Values of $\chi_\alpha^2(n_1)$ corresponding to $\alpha = 0.01, 0.02, 0.05, 0.10, 0.20, 0.30, 0.50, 0.70, 0.80, 0.90, 0.95, 0.98$, and 0.99 are given to 3 decimals for $n_1 = 1$ to 30 by steps of 1 in Table III of Fisher, *Statistical Methods* and in Table IV of Fisher and Yates, *Statistical Tables*, the latter of which also contains the values for $\alpha = 0.001$. Values of $\chi_\alpha^2(n_1)$ corresponding to $\alpha = 0.005, 0.010, 0.025, 0.050, 0.100, 0.250, 0.500, 0.750, 0.900, 0.950, 0.975, 0.990$, and 0.995 are given to 6 significant figures for $n_1 = 1$ to 30 by steps of 1 and from 30 to 100 by steps of 10 by Thompson, " χ^2 distribution."

Table 8.1. The corresponding values of $\rho(0.01, \beta, n)$ are given in Table 8.2. The values of $\rho(\alpha, \beta, n)$ for $n = 120$ were computed from values of $\chi^2_\alpha(120)$ obtained from the percentage points of the F distribution tabled by Merrington and Thompson, by means of the relation

$$\chi^2_\alpha(n) = nF_\alpha(n, \infty) \quad (44)$$

Two-point interpolation in Tables 8.1 and 8.2 in terms of the argument $1/\sqrt{n}$ will yield about 2-decimal accuracy in most parts of these tables.*

6.2. Method of Construction and Accuracy of Tables 8.3 and 8.4

The procedure described in Sec. 4.1 for determining whether a particular one of two new products or processes is more variable than the other is as follows: Compute the statistic s_1^2/s_2^2 , where s_1^2 and s_2^2 are sample estimates of the two population variances such that in repeated sampling $n_1 s_1^2/\sigma_1^2$ and $n_2 s_2^2/\sigma_2^2$ will be distributed independently as χ^2 for n_1 and n_2 degrees of freedom, respectively. Base the choice of product or process on the rule

(a) Accept product I whenever

$$\frac{s_1^2}{s_2^2} \leq F_\alpha(n_1, n_2) \quad (45)$$

(b) Accept product II whenever

$$\frac{s_1^2}{s_2^2} > F_\alpha(n_1, n_2) \quad (46)$$

where $F_\alpha(n_1, n_2)$ is the α level of significance of the variance ratio (F) distribution. This rule is so formulated that the probability of accepting product II when in fact $\sigma_1^2/\sigma_2^2 = 1$ (error of the first kind) equals the level of significance α . The probability of accepting product I when in fact $\sigma_1^2 > \sigma_2^2$ (error of the second kind) depends on the ratio $\phi = \sigma_1^2/\sigma_2^2$ and is exactly β when

$$\begin{aligned} \phi(\alpha, \beta, n_1, n_2) &= \frac{F_\alpha(n_1, n_2)}{F_{1-\beta}(n_1, n_2)} \\ &= F_\alpha(n_1, n_2) \cdot F_\beta(n_2, n_1) \end{aligned} \quad (47)$$

The proof is similar to the proof of (40). Product I will be chosen whenever (45) occurs, and the probability of this when $\sigma_1^2/\sigma_2^2 = \phi$ is

* Interpolation with respect to α and β should be carried out in terms of K_α and K_β , respectively, where K_ϵ is the unit normal deviate exceeded with probability ϵ (tabled in Chap. 1, Table 1.1). For an explanation and examples of this type of interpolation, see Simaika, *Interpolation*.

$$\begin{aligned}
 P \left\{ \frac{s_1^2}{s_2^2} \leq F_\alpha(n_1, n_2) \left| \frac{\sigma_1^2}{\sigma_2^2} = \phi \right. \right\} &= P \left\{ \frac{\frac{s_1^2}{\sigma_1^2}}{\frac{s_2^2}{\sigma_2^2}} \leq \frac{F_\alpha(n_1, n_2) \frac{\sigma_1^2}{\sigma_2^2}}{\phi} = \phi \right\} \\
 &= P \left\{ F(n_1, n_2) \leq \frac{F_\alpha(n_1, n_2)}{\phi} \right\} \\
 &= 1 - P \left\{ F(n_1, n_2) > \frac{F_\alpha(n_1, n_2)}{\phi} \right\} \\
 &= 1 - (1 - \beta) = \beta
 \end{aligned} \tag{48}$$

when*

$$\frac{F_\alpha(n_1, n_2)}{\phi} = F_{1-\beta}(n_1, n_2) \tag{49}$$

Tables 8.3 and 8.4 at the end of this chapter were computed from the Merrington-Thompson table of F by direct substitution in formula (47). These tables give the values of $\phi(\alpha, \beta, n_1, n_2)$ for $\alpha = 0.050$ and $\alpha = 0.010$, respectively, corresponding to $\beta = 0.005, 0.010, 0.025, 0.050, 0.100, 0.250, 0.500, 0.750, 0.900, 0.950, 0.975, 0.990, 0.995$, for $n_1 = 1$ to 10 by steps of 1, and 12, 15, 20, 24, 30, 40, 60, 120, ∞ , and $n_2 = 1$ to 10 by steps of 1, and 12, 15, 20, 24, 30, 40, 60, 120, ∞ . Interpolation for values of $\phi(\alpha, \beta, n_1, n_2)$ corresponding to values of n_1 and n_2 between those given in these tables should be done harmonically, that is, in terms of $1/n_1$ and $1/n_2$. In this connection it should be noted that the sequence $\infty, 120, 60, 40, 30, 24, 20$ corresponds to $120/m$ for $m = 0, 1, 2, 3, 4, 5$, and 6, respectively; and that the sequence $\infty, 60, 30, 20, 15, 12, 10$ corresponds to $60/r$ for $r = 0, 1, 2, 3, 4, 5$, and 6, respectively. Accordingly, interpolation is most conveniently carried out in terms of the arguments m and r . Two-point harmonic interpolation will generally give ϕ to sufficient accuracy for most practical purposes. For example, by 2-point harmonic interpolation

$$\phi(0.05, 0.05, 30, 24) = \frac{\phi(0.05, 0.05, 30, 20) + \phi(0.05, 0.05, 30, 30)}{2} = 3.664 \tag{50}$$

The actual value is 3.660; customary 2-point linear interpolation gives

* The most accurate table of $F_\alpha(n_1, n_2)$ is that of Merrington and Thompson, which gives the values to 5 significant figures corresponding to $\alpha = 0.005, 0.010, 0.025, 0.050, 0.100, 0.250$, and 0.500 for $n_1 = 1$ to 10 by steps of 1, and 12, 15, 20, 24, 30, 40, 60, 120, ∞ , and $n_2 = 1$ to 30 by steps of 1, and 40, 60, 120, ∞ . Values of $F_\alpha(n_1, n_2)$, referred to as e^{22} , corresponding to $\alpha = 0.001, 0.01, 0.05, 0.20$, are given (mostly to 2 decimals) in Table V of Fisher and Yates, *Statistical Tables* for $n_1 = 1$ to 6 by steps of 1, and 8, 12, 24, ∞ , and $n_2 = 1$ to 30 by steps of 1, and 40, 60, 120, ∞ .

3.719. Similarly, by 2-point harmonic interpolation

$$\phi(0.05, 0.05, 30, 120) \doteq \frac{\phi(0.05, 0.05, 30, 60) + \phi(0.05, 0.05, 30, \infty)}{2} = 2.618 \quad (51)$$

The actual value is 2.617. Use may be made of the fact that

$$\phi(\alpha, \beta, n_1, \infty) = \rho(\alpha, \beta, n_1) \quad (52)$$

to obtain values of the left side of this equality for values of n_1 included in Tables 8.1 and 8.2 but not in Tables 8.3 and 8.4.

7. REFERENCES*

- BAINES, A. H. J.: *On Economical Design of Statistical Experiments*, (British) Ministry of Supply, Advisory Service on Statistical Method and Quality Control, Technical Report, Series R, No. Q.C./R/15, July 15, 1944.
- DANIELS, H. E.: "The Estimation of Components of Variance," *Supplement to the Journal of the Royal Statistical Society*, Vol. 6 (1939), pp. 186-197.
- FISHER, R. A.: *Statistical Methods for Research Workers*, 5th and later ed., Oliver and Boyd, Ltd., Edinburgh and London, 1934-1944.
- , and YATES, FRANK: *Statistical Tables for Biological, Agricultural and Medical Research*, 2d ed., Oliver and Boyd, Ltd., London and Edinburgh, 1943, 98 + viii pp.
- MERRINGTON, MAXINE, and THOMPSON, CATHERINE M.: "Tables of Percentage Points of the Inverted Beta (F) Distribution," *Biometrika*, Vol. 33 (1943), pp. 73-88.
- NEYMAN, J., and PEARSON, E. S.: "On the Use and Interpretation of Certain Test Criteria for Purposes of Statistical Inference," *Biometrika*, Vol. 20A (1928), pp. 175-240, 263-294.
- SIMAICA, J. B.: "Interpolation for Fresh Probability Levels between the Standard Table Levels of a Function," *Biometrika*, Vol. 32 (1941), pp. 263-276.
- THOMPSON, CATHERINE M.: "Table of Percentage Points of the χ^2 Distribution," *Biometrika*, Vol. 32 (1941), pp. 187-191.

* While this volume was in press there appeared a paper by C. D. Ferris, F. E. Grubbs, and C. L. Weaver, "Operating Characteristics for the Common Statistical Tests of Significance," *Annals of Mathematical Statistics*, Vol. 17 (1946), pp. 178-197. Fig. 1, p. 181, of the paper gives operating-characteristic curves similar to those of Fig. 8.1 of this chapter, for $n_1 = 2$ to 10, 15, 20 to 50 by steps of 10, 75, and 100. Curves similar to those of Fig. 8.3 are given in Fig. 3, p. 185, for $n_1 = n_2 = 2$ to 10, 15, 20 to 50 by steps of 10, 75, and 100, in Fig. 4, p. 186, for certain cases in which $3n_1 = 2n_2$ or $2n_1 = n_2$, and in Fig. 5, p. 187, for certain cases in which $2n_1 = 3n_2$ or $n_1 = 2n_2$.

CHAPTER 9

UTILIZATION OF LIMITED EXPERIMENTAL FACILITIES WHEN THE COST OF EACH MEASUREMENT DEPENDS ON ITS MAGNITUDE

	PAGE
1. Type of Problem.	321
2. Specific Problem	322
3. Solution.	322
4. Mathematical Development	324
4.1 Notation.	324
4.2 Objective to Get Best Estimate of Slope	325
4.3 Objective to Get Best Estimate of Time to Rupture at a Given Stress.	327
5. Reference	328

This chapter was prepared by
Milton Friedman, University of Chicago

CHAPTER 9

UTILIZATION OF LIMITED EXPERIMENTAL FACILITIES WHEN THE COST OF EACH MEASUREMENT DEPENDS ON ITS MAGNITUDE

1. TYPE OF PROBLEM

A primary objective in the statistical design of experiments is to maximize the amount of pertinent information obtained from a given amount of time, equipment, personnel, and supplies, or, conversely, to minimize the cost of obtaining a given amount of information. In many experiments the cost of an observation can be regarded as a constant; such is the case, for example, in the problem of Chap. 11. Sometimes the cost of an observation is determined by the independent variables, as, for example, when an independent variable is the amount of some expensive substance or type of energy. This chapter is concerned with a third situation, in which the cost of an observation depends on the value of the dependent variable; a simple case occurs when the dependent variable is determined by counting, so that the time and labor involved in a measurement are proportional to its magnitude. Insofar as the dependent and independent variables are correlated, the latter two situations are essentially the same.

An interesting case in which the cost of an observation depends on its magnitude, one which illustrates the interplay of statistical principles and substantive considerations in applied statistics, occurs in metallurgical experiments to determine the relation between time to rupture and stress for a given alloy. In investigating this relation, each observation is obtained by subjecting a test specimen to a predetermined constant stress and recording the amount of time that elapses before the specimen breaks. The number of observations that can be obtained in a given period of time from a single piece of equipment thus depends on how long it takes each specimen to rupture, which in turn depends largely on the stress to which the test specimen is subjected.

If the logarithm of time to rupture is a linear function of the logarithm of stress (and there is strong evidence that this is approximately so for a large number of alloys over the range of important stresses), tests at any two stresses suffice to estimate the line relating the two variables, and from this line can be predicted the time to rupture at any other stress. The error in such a prediction depends on the number of tests from which the line is estimated and on the stresses at which they are

made. But the number of tests made itself depends on the stresses at which they are made, since the lower the stress, the longer it takes for a specimen to break, and hence the fewer the tests that can be made in a limited period with given equipment. This factor, taken by itself, would argue for using as high stresses as possible, in order to have many tests. However, the higher the stresses, the farther it is necessary to extrapolate the line to predict time to rupture at the stresses which are practically important. Further, while the percentage error in test results seems reasonably independent of the stress used for a fairly wide range of stresses, it will doubtless increase if the stress is raised sufficiently. Thus there is a real problem about the best stresses at which to test; there are opposing considerations that have to be evaluated quantitatively to get a definite answer.

2. SPECIFIC PROBLEM

It will facilitate the solution of the problem to state it more formally, as follows:

Given: (1) The relation between time to rupture and stress is

$$t = \alpha + \beta s \quad (1)$$

where t is the logarithm of time to rupture, s is the logarithm of the stress, and α and β are constants describing the "true" (but unknown) relationship.

(2) The number of specimens that can be tested is limited solely by the fact that there are a limited number of machines available and a limited amount of time.

(3) The percentage error in the determination of time to rupture does not depend on stress; that is, if a great many determinations were made at each of a number of stresses, the percentage variation in the determinations would be the same at all stresses. This assumption will undoubtedly break down at sufficiently high stresses, but it seems to be confirmed by the available evidence for stresses ordinarily used.

Required: (1) The stresses at which to make the tests, and (2) the best apportionment of the tests among these stresses, in order to estimate as accurately as possible (a) the slope β of the line relating t to s , and (b) the time to rupture at some predetermined stress, or range of stresses, of practical importance, ordinarily considerably below the stresses at which the tests are conducted.

3. SOLUTION

The solution of this problem is as follows:

(1) It is always better to use two testing stresses than to use more than two.

(2) For purpose (b) it might sometimes be best to use only one stress S_0 of practical importance. However, since this would give no information about the time to rupture at any other stress, it would ignore purpose (a) and is therefore excluded.

(3) Let S_1 and S_2 be the two best testing stresses ($S_2 > S_1$). Then the best ratio of the two stresses, say, $R = S_1/S_2$, is given by solving the following equation for R :

$$\frac{\beta}{2} \log_e R = 1 + R^{-\frac{\beta}{2}} \quad (2)$$

This is the best ratio both for estimating the slope and for estimating the time to rupture at S_0 , provided S_0 is less than S_1 , the case of primary interest.* The best ratio of the two testing stresses is therefore independent of S_0 and depends only on β . The value of β is, of course, to be determined from the experiment; but some advance estimate is needed because the relative times required for tests at two different stresses depend on β . However, the advance estimate need not be very accurate, since even fairly large errors in the estimate of β will not lead to any great loss in efficiency.

(4) Under the given assumptions, the absolute values of S_1 and S_2 cannot be determined. So long as assumption (3) of Sec. 2 is satisfied, namely, that the percentage error is independent of stress, the higher the testing stresses the better. In practice, therefore, S_2 should be chosen as the highest testing stress for which the percentage error can reasonably be expected to be no larger than at lower stresses. S_1 can then be determined from the R given by equation (2).

(5) Let n_1 be the number of tests to be made at S_1 and n_2 the number to be made at S_2 . Let $r = n_1/n_2$. The ratio r is all that needs to be determined, since the total number of tests, $n_1 + n_2$, is determined by S_1 and S_2 and by the time and equipment available. The best value of r depends on the objective. If the objective is to estimate β as accurately as possible, the best value of r is given by

$$r = R^{-\frac{\beta}{2}} \quad (3)$$

If the objective is to estimate the time to rupture at S_0 as accurately as possible, the best value of r is given by

$$r = R^{-\frac{\beta}{2}} \frac{\log \frac{S_0}{S_2}}{\log \frac{S_0}{S_1}} \quad (4)$$

* See Sec. 4.3, especially the last paragraph, for a discussion of the case where $S_1 \leq S_0$.

The best value of r in this case depends on S_0 . This means that it is not possible to design the experiment so as to get the best estimate of the time to rupture at each of a range of S_0 's. It is necessary to compromise among the objectives.

(6) The following numerical calculation illustrates the solution. For one particular series of cast alloys tested at a particular elevated temperature, β is found to be approximately -8 . If S_2 is taken as 30,000 pounds per square inch (p.s.i.), the best value of S_1 turns out to be 22,000 p.s.i. The best apportionment of the tests between the two stresses is as follows:

Objective is to estimate as accurately as possible	Number of tests to be made at 22,000 p.s.i. for each test at 30,000 p.s.i.	Percentage gain in precision over using 0.50 tests at 25,000 p.s.i. for every test at 30,000 p.s.i.
(a) Slope.....	0.26	39
(b) Time to rupture at stress of		
5,000 p.s.i.	0.35	42
10,000 p.s.i.	0.41	45
15,000 p.s.i.	0.53	47
20,000 p.s.i.	1.25	55

The last column gives the gain in precision, which is equivalent to the savings in testing for a given degree of precision, over an alternative combination of stresses and relative number of observations, which differs only moderately from the optimum combination; it indicates the value of careful planning of the stresses at which to test and of the relative number of tests at different stresses.

4. MATHEMATICAL DEVELOPMENT

4.1. Notation

Let T = time to rupture

t = logarithm of time to rupture

S = stress

S_0 = stress for which it is desired to estimate time to rupture

S_1 = smaller of two testing stresses to be used

S_2 = larger of two testing stresses to be used

n_1 = number of tests to be made at S_1

n_2 = number of tests to be made at S_2

$n = n_1 + n_2$

$R = S_1/S_2$

$r = n_1/n_2$

α, β = parameters of line relating $\log T$ to $\log S$, so that

$$\log T = \alpha + \beta \log S \quad (5)$$

a, b = estimates of α and β

t_0 = estimate of logarithm of time to rupture at stress S_0

K = total amount of machine time available

σ = standard deviation of observations about the line (5), assumed the same for all S

σ_b = standard deviation of estimated slope

σ_{t_0} = standard deviation of logarithm of estimated time to rupture

For convenience, take all logarithms to be natural logarithms.

We assume that the parameters of the line are estimated from the data by the usual least-squares procedure applied to the logarithms of the variables. Then, by algebraic manipulation of the usual formulas,*

$$\sigma_b^2 = \frac{\sigma^2}{\frac{n_1 n_2}{n_1 + n_2} \left(\log \frac{S_1}{S_2} \right)^2} \quad (6)$$

$$\sigma_{t_0}^2 = \sigma^2 \left[\frac{n_1 \left(\log \frac{S_0}{S_1} \right)^2 + n_2 \left(\log \frac{S_0}{S_2} \right)^2}{n_1 n_2 \left(\log \frac{S_1}{S_2} \right)^2} \right] \quad (7)$$

The problem is to minimize (6) and (7) by proper choice of n_1 , n_2 , S_1 , and S_2 , subject to the constraint that a fixed amount of machine time is used. Since $T = e^\alpha S^\beta$, this constraint is

$$n_1 e^\alpha S_1^\beta + n_2 e^\alpha S_2^\beta = K \quad (8)$$

or

$$n_1 S_1^\beta + n_2 S_2^\beta = K e^{-\alpha} = k \quad (9)$$

It will clarify the solution and yield useful supplementary results to proceed to the final solution in stages, rather than at one step. We shall, therefore, first assume S_1 and S_2 given and determine the optimum value of r ; thereafter we shall proceed to determine the optimum value of R .

4.2. Objective to Get Best Estimate of Slope

The problem is to maximize

$$\frac{\sigma^2}{\sigma_b^2} = \frac{n_1 n_2}{n_1 + n_2} \left(\log \frac{S_1}{S_2} \right)^2 \quad (10)$$

subject to (9), since this will minimize the variance of the slope as given by (6).

Replacing n_1 by $r n_2$ in (9) and (10), solving (9) so modified for n_2 , and substituting the result for n_2 in (10) gives

$$\frac{\sigma^2}{\sigma_b^2} = \frac{k r \left(\log \frac{S_1}{S_2} \right)^2}{(1 + r)(r S_1^\beta + S_2^\beta)} \quad (11)$$

* See FISHER, *Statistical Methods*, Sec. 26, pp. 133, 135. (For full citation, see Sec. 5.)

to be maximized with respect to r , without restraint and with S_1 and S_2 assumed fixed. Setting the derivative with respect to r equal to zero gives

$$\frac{d\left(\frac{\sigma_b^2}{\sigma^2}\right)}{dr} - k\left(\log \frac{S_1}{S_2}\right)^2 \frac{(S_2^\beta - r^2 S_1^\beta)}{(1+r)^2(rS_1^\beta + S_2^\beta)^2} = 0 \quad (12)$$

A solution to (12) is obtained by setting

$$S_2^\beta - r^2 S_1^\beta = 0 \quad (13)$$

or

$$r = \left(\frac{S_1}{S_2}\right)^{-\frac{\beta}{2}} = R^{-\frac{\beta}{2}} \quad (14)$$

where we take the positive square root, as r is essentially positive. A check on the second derivative shows that this solution does maximize (11). Substituting (14) into (11) and taking the reciprocal gives

$$\frac{\sigma_b^2}{\sigma^2} = \frac{(S_1^{\frac{\beta}{2}} + S_2^{\frac{\beta}{2}})^2}{k\left(\log \frac{S_1}{S_2}\right)^2} \quad (15)$$

as the minimum ratio of the variance of the estimated slope to the variance of an individual observation, given S_1 and S_2 .

Replacing S_1 by RS_2 in (15) gives

$$\frac{\sigma_b^2}{\sigma^2} = \frac{(R^{\frac{\beta}{2}} + 1)^2 S_2^\beta}{k(\log R)^2} \quad (16)$$

Consider S_2 as fixed and minimize (16) with respect to R ; this gives

$$\frac{d\left(\frac{\sigma_b^2}{\sigma^2}\right)}{dR} = \frac{2S_2^\beta (R^{\frac{\beta}{2}} + 1)}{kR(\log R)^3} \left[\frac{\beta}{2} R^{\frac{\beta}{2}} \log R - R^{\frac{\beta}{2}} - 1 \right] = 0 \quad (17)$$

whence

$$\frac{\beta}{2} \log R = 1 + R^{-\frac{\beta}{2}} \quad (18)$$

A check on the second derivative shows that this solution does minimize (16).

Substituting the value for $\log R$ from (18) in (16) gives

$$\frac{\sigma_b^2}{\sigma^2} = \frac{\beta^2 R^\beta S_2^\beta}{4k} \quad (19)$$

as the minimum value of (16), given S_2 . Since β is negative, it is clear that the larger S_2 , the smaller the variance; hence there is no finite optimum value of S_2 . In practice, increases in S_2 beyond some point will increase σ^2 , and the optimum value of S_2 will be somewhere near this point.*

4.3. Objective to Get Best Estimate of Time to Rupture at a Given Stress

The problem here is to minimize (7) subject to (9). Replacing n_1 by rn_2 in (7) and (9), solving (9) so modified for n_2 , and substituting the result in (7) gives

$$\frac{\sigma_{t_0}^2}{\sigma^2} = \frac{\left[r \left(\log \frac{S_0}{S_1} \right)^2 + \left(\log \frac{S_0}{S_2} \right)^2 \right] [rS_1^\beta + S_2^\beta]}{kr \left(\log \frac{S_1}{S_2} \right)^2} \quad (20)$$

to be minimized with respect to r , without restraint and with S_1 and S_2 assumed fixed. Setting the derivative of (20) with respect to r equal to zero gives

$$\frac{d \left(\frac{\sigma_{t_0}^2}{\sigma^2} \right)}{dr} = \frac{1}{kr^2 \left(\log \frac{S_1}{S_2} \right)^2} \left[r^2 S_1^\beta \left(\log \frac{S_0}{S_1} \right)^2 - S_2^\beta \left(\log \frac{S_0}{S_2} \right)^2 \right] = 0 \quad (21)$$

From (21) the minimizing solution is given by

$$r^2 = \left(\frac{S_2}{S_1} \right)^\beta \left(\frac{\log \frac{S_0}{S_2}}{\log \frac{S_0}{S_1}} \right)^2 \quad (22)$$

or

$$r = \pm \left(\frac{S_2}{S_1} \right)^{\frac{\beta}{2}} \frac{\log \frac{S_0}{S_2}}{\log \frac{S_0}{S_1}} \quad (23)$$

The positive sign is required to make r positive if S_0 is less than S_1 or greater than S_2 ; the negative sign, if $S_1 < S_0 < S_2$. The second derivative shows that these signs also give minima. Since we are concerned primarily with values of S_0 that are below S_1 , we shall hereafter consider only the positive sign.

* It will pay to go somewhat beyond the point at which σ^2 starts to increase, since the loss from the increase in σ^2 will for a time be less than the gain from the increase in S_2 .

Substituting (23) into (20) gives as the minimum ratio of the variance of the estimated rupture time to the variance of an individual observation, with S_1 and S_2 fixed,

$$\frac{\sigma_{i_0}^2}{\sigma^2} = \frac{\left[S_1^{\frac{\beta}{2}} \log \frac{S_0}{S_2} + S_2^{\frac{\beta}{2}} \log \frac{S_0}{S_1} \right]^2}{k \left(\log \frac{S_1}{S_2} \right)^2} \quad (24)$$

On replacing S_1 by RS_2 , (24) becomes

$$\frac{\sigma_{i_0}^2}{\sigma^2} = \frac{S_2^{\frac{\beta}{2}}}{k} \left[\frac{(1 + R^{\frac{\beta}{2}}) \log \frac{S_0}{S_2}}{\log R} - 1 \right]^2 \quad (25)$$

from which, holding S_2 fixed,

$$\begin{aligned} \frac{d \left(\frac{\sigma_{i_0}^2}{\sigma^2} \right)}{dR} &= \frac{2S_2^{\frac{\beta}{2}}}{k} \left[\frac{(1 + R^{\frac{\beta}{2}}) \log \frac{S_0}{S_2}}{\log R} - 1 \right] \left[\frac{\left(\frac{\beta}{2} R^{\frac{\beta}{2}} \log R - 1 - R^{\frac{\beta}{2}} \right) \log \frac{S_0}{S_2}}{R (\log R)^2} \right] \\ &= 0 \end{aligned} \quad (26)$$

For S_0 less than S_1 , there is no value of R that will make the first bracket equal to zero. Accordingly, the minimizing value of R is given by

$$\frac{\beta}{2} R^{\frac{\beta}{2}} \log R - 1 - R^{\frac{\beta}{2}} = 0 \quad (27)$$

or

$$\frac{\beta}{2} \log R = 1 + R^{-\frac{\beta}{2}} \quad (28)$$

which is the same as (18), the solution for minimizing the variance of the slope. This is, of course, the minimizing value only if S_2 is sufficiently large so that the derived S_1 is larger than S_0 .

By differentiating (25) with respect to S_2 , it can be shown that (25) decreases as S_2 increases, so that there is no finite optimum value of S_2 .

If S_2 is chosen greater than S_0 , while S_1 derived from the R satisfying (28) is less than S_0 , (28) no longer gives the optimum solution. In that case, it turns out that the variance is a monotonically decreasing function of R . The best that can be done is to take the largest possible value of R , namely, $R = S_0/S_2$, or $S_1 = S_0$. This solution using two testing stresses will not, however, be as good as that putting all the tests at S_0 .

5. REFERENCE

FISHER, R. A.: *Statistical Methods for Research Workers*, 4th and later ed., Oliver and Boyd, Ltd., Edinburgh and London, 1932-1944.

CHAPTER 10 EXPERIMENTS IN WHICH THE INDEPENDENT VARIABLE IS KNOWN ONLY IN TERMS OF A PROBABILITY DISTRIBUTION

	PAGE
1. Problem	331
1.1 Type of Problem	331
1.2 Specific Problem	331
2. Solution.	332
3. Confidence Limits for Proportion Defective	333
3.1 Attributes	333
3.2 Variables.	336
4. Size of Preliminary Sample	336
5. References.	338

FIGURES

10.1 Ninety-nine percent Confidence Belts for Population Proportion	332
10.2 Ninety-five percent Confidence Belts for Population Proportion	333
10.3 Ninety percent Confidence Belts for Population Proportion	334
10.4 Eighty percent Confidence Belts for Population Proportion	335

This chapter was prepared by the editors.

With the exception of the charts and related material, it is based on a memorandum by J. Wolfowitz, Columbia University

CHAPTER 10

EXPERIMENTS IN WHICH THE INDEPENDENT VARIABLE IS KNOWN ONLY IN TERMS OF A PROBABILITY DISTRIBUTION

1. PROBLEM

1.1. Type of Problem

This chapter deals with a type of problem in which it is desired to subject each of a number of items to a test of at least a given severity, but the severity of any one test cannot be measured and cannot be controlled precisely. Thus it is necessary to make an independent study of the probability that a test will attain the specified severity and then to determine the number of tests necessary for each item in order to attain a given probability that at least one test will be of the specified severity. The particular problem discussed is relatively simple, and the chapter is intended more to suggest an interesting and in some respects important type of problem and to indicate an approach to it, than to present a solution or a novel application of statistical techniques.

1.2. Specific Problem

A gun barrel is considered fit for service with respect to its pressure-resisting properties if it has fired a round such that the gas pressure developed is not less than a prescribed pressure K , K being greater than any pressure that may reasonably occur in service. Special ammunition that develops high pressures is used for proofing the barrels. In order to measure the pressure developed by a round, a hole must be bored in the barrel, which renders it unfit for service. Consequently, it is impossible to ascertain with certainty that a barrel intended for service has actually been proofed. It is, however, possible to draw conclusions about the percentage of barrels proofed from a study of the characteristics of the special ammunition. When a lot of the latter is delivered, a small fixed sample of size n is tested for pressure and the remainder (which is almost the whole lot) is used for proofing, N rounds being fired in each barrel to be proofed. Manufacture of the special ammunition is in a sufficiently satisfactory state that the proportion of defective rounds, that is, those which generate a pressure less than K , is usually very small (of the order of 0.001). The problem is, on the basis of the results from the sample of n , (1) to set up criteria for accepting or rejecting the lot, and (2) to determine N , the number of rounds to be fired in each barrel.

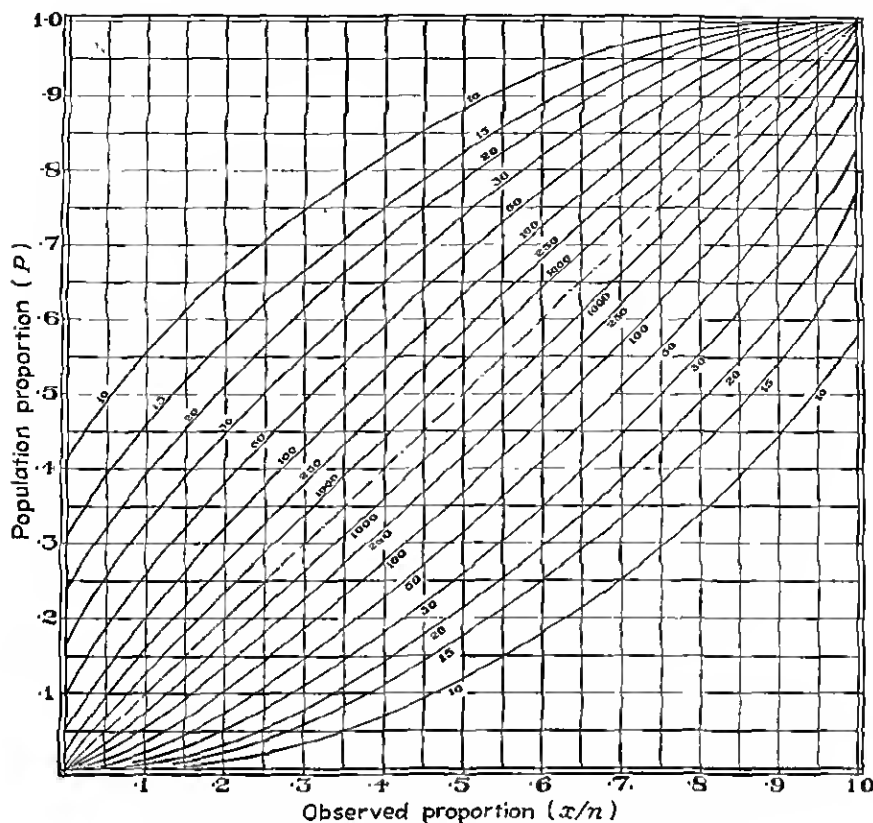


FIG. 10.1.—Ninety-nine percent confidence belts for population proportion.

2. SOLUTION

Choose γ , a confidence coefficient with which to operate, the minimum number of barrels that an acceptable lot should proof, and the minimum tolerable probability of proofing a barrel. From the sample of n obtain an estimate \hat{p}_γ with confidence coefficient γ of an upper bound on the proportion of rounds in the lot which, when fired, will generate a pressure less than K . How this estimate is to be obtained is described in Sec. 3. Construct a table as follows:

Number of rounds (N) fired in each barrel	With confidence coefficient γ , the probability that a barrel will be proofed is at least
1	$1 - \hat{p}_\gamma$
2	$1 - \hat{p}_\gamma^2$
...	...
i	$1 - \hat{p}_\gamma^i$
...	...

From the table select the smallest N yielding the required probability of proofing a barrel. If this N is too large to enable the lot of ammunition

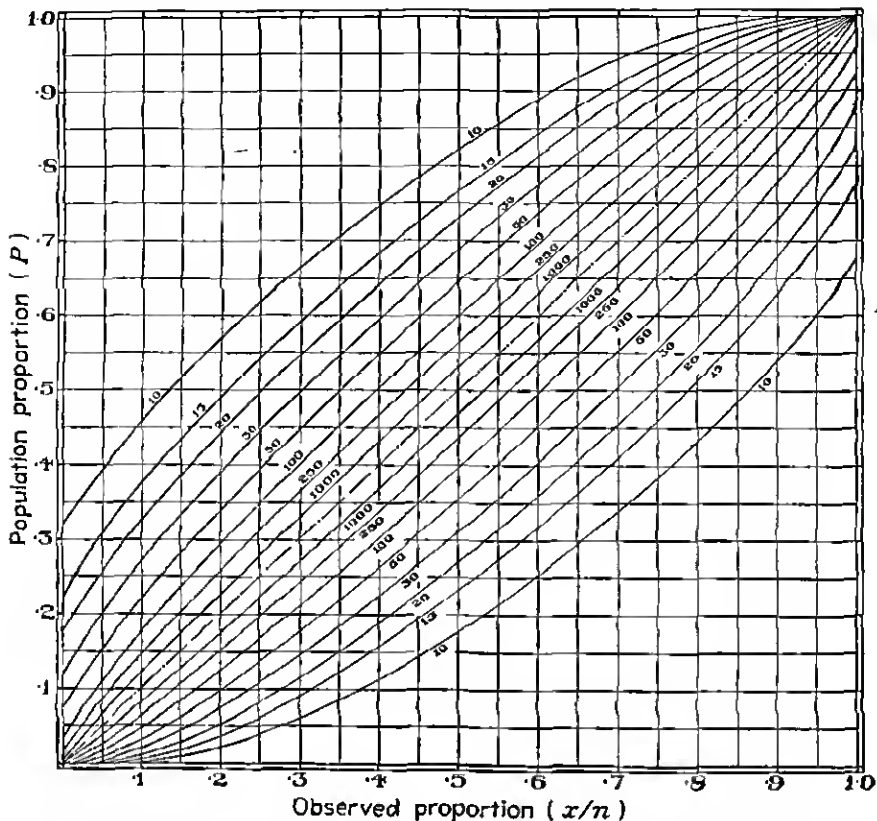


FIG. 10.2.—Ninety-five percent confidence belts for population proportion.

to proof the minimum required number of barrels, reject the lot. Otherwise, fire N rounds in each barrel.

3. CONFIDENCE LIMITS FOR PROPORTION DEFECTIVE

3.1. Attributes

If the upper confidence limit \hat{p}_r is determined by attributes, that is, by classifying each round in the sample of n as above K or below K , it is unnecessary to make any assumption, whatever about the distribution of the pressures of the bullets of the lot. It is only necessary that the sample of n be selected at random. If it is believed that defective rounds do not occur independently (for example, if a machine functions improperly, all the bullets it produces may be defective and these may be adjacent in the lot), the N bullets to be fired from any gun barrel should be chosen at random from the lot.

Perhaps the most accurate convenient method of finding \hat{p}_γ is with the aid of Thompson's table of percentage points of the incomplete beta function. Let

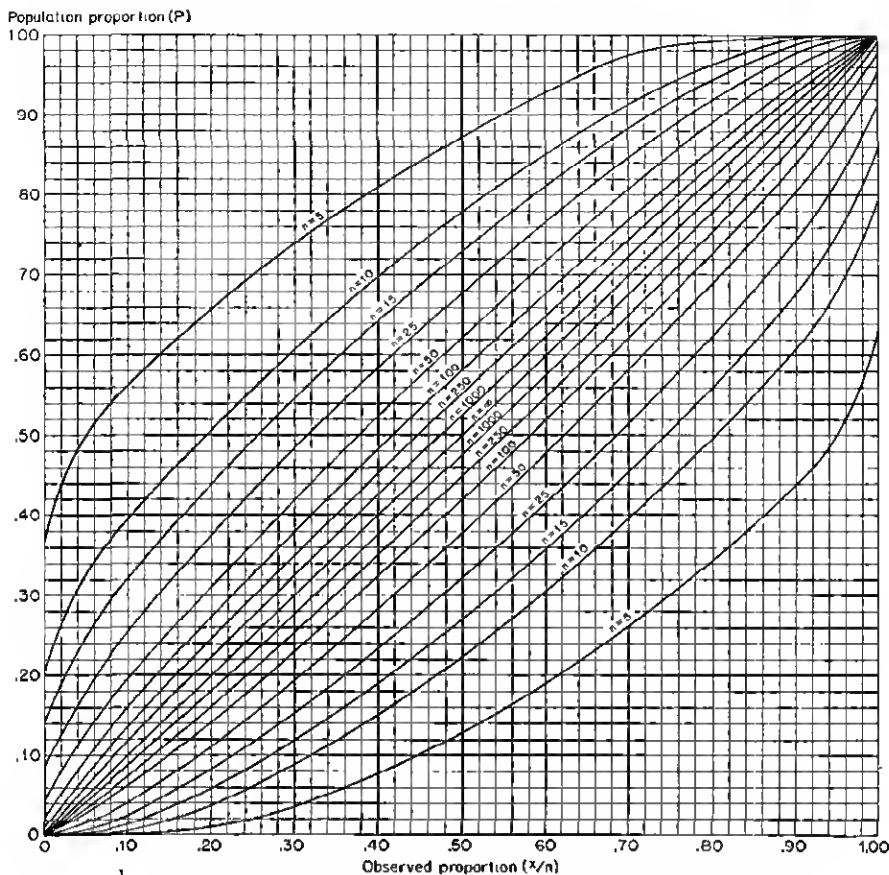


FIG. 10.3.—Ninety percent confidence belts for population proportion.

c = number of rounds in the sample of n
 whose pressures are less than K (1)

$$\alpha = 100(1 - \gamma) \quad (2)$$

$$\nu_1 = 2(c + 1) \quad (3)$$

$$\nu_2 = 2(n - c) \quad (4)$$

Enter the table with ν_1 and ν_2 on the α percentage-point page and find x . Then $\hat{p}_\gamma = 1 - x$. For example, if $\gamma = 0.975$, $c = 0$, $n = 30$, we have $\alpha = 2.5$, $\nu_1 = 2$, $\nu_2 = 60$; from the table we find $x = 0.88430$, or $\hat{p}_{0.975} = 0.1157$. The table of Sec. 2 then appears as follows:

N	Minimum probability
1	0.8843
2	0.9866
3	0.9985
etc.	

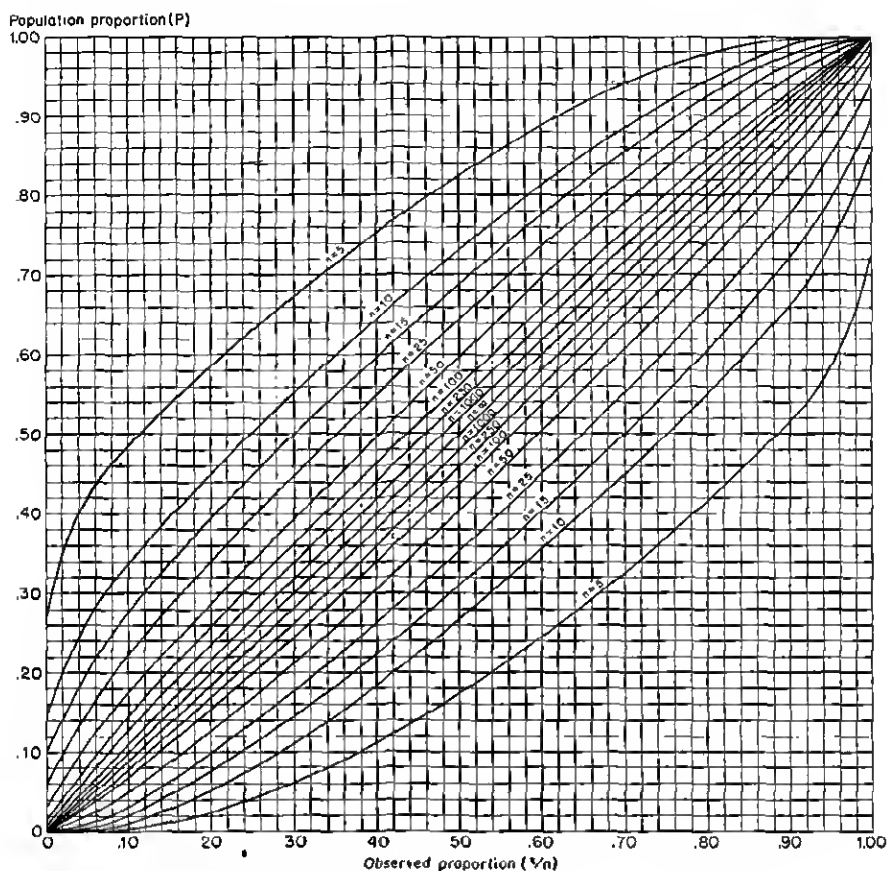


FIG. 10.4.—Eighty percent confidence belts for population proportion.

Note: When $c = 0$, $\hat{p}_\gamma = 1 - (1 - \gamma)^{\frac{1}{n}}$.

When $\gamma = 0.995, 0.975, 0.95$, or 0.90 , \hat{p}_γ may be found from Figs. 10.1, 10.2, 10.3, or 10.4.* These show belts within which we may assert,

* Figures 10.1 and 10.2 are reproduced from Pearson and Clopper, "Confidence Limits," by permission of *Biometrika*. Figures 10.3 and 10.4 are based on computations from Thompson's "Incomplete Beta Function" made (in cooperation with the Statistical Research Group) by R. L. Deckinger of the Bureau of Ordnance, U.S. Navy, and furnished through the courtesy of R. H. Park. (For full citations, see Sec. 5.)

With regard to Figs. 10.1 and 10.2, Professor E. S. Pearson writes in part: "Actually I believe they are not completely accurate, as the levels at certain points were obtained by interpolation and not by direct calculation from the 'Incomplete Beta Function.' If we reproduce such diagrams ourselves, we shall have to look into this point." (Letter of January 16, 1946, to one of the editors.)

For Figs. 10.3 and 10.4, abscissas were computed for ordinates between 0 and 1 by

with confidence coefficient of, say, Γ , that the true proportion lies when the observed proportion is x/n . For the present purposes γ is related to Γ by

$$\Gamma = 2\gamma - 1 \quad (5)$$

Thus, for the example of the preceding paragraph (where $\gamma = 0.975$), $\Gamma = 0.95$. From Fig. 10.2 we see that the upper curve for $n = 30$ cuts the axis $x/n = 0$ at about 0.11 or 0.12.

Still another method of finding \hat{p}_γ is by means of the arcsin transformation described in Chap. 16. Thus

$$\hat{p}_\gamma = \sin^2 \left(\arcsin \sqrt{\frac{c}{n}} + \frac{K_{1-\gamma}}{2\sqrt{n}} \right) \quad (6)$$

where $K_{1-\gamma}$ is the normal deviate exceeded with probability $1 - \gamma$ (see Table 1.1 of Chap. 1). This formula is not satisfactory, however, when c/n is very small, especially not when $c = 0$.

It should be noted that the foregoing assumes the lot to be large enough relative to the sample so that the effect of lot size can be ignored; this will almost always be the case in practice.

3.2. Variables

If it can be assumed that the gas pressures of the bullets in the lot are random independent observations on a normally distributed variate, \hat{p}_γ can be determined by the method described in Chap. 1, Sec. 8.2 (pp. 42-45).^{*} The value of Γ given by equation (5) of this chapter is used as the value of γ in Chap. 1; in other words, L_p of Chap. 1 corresponds with $1 - \gamma$ of this chapter.

4. SIZE OF PRELIMINARY SAMPLE

While the rounds expended in testing the initial sample of n do not serve directly to proof machine-gun barrels, it would be an error to

steps of 0.1, using Thompson's "Incomplete Beta Function." For a confidence coefficient Γ (in Fig. 10.3, $\Gamma = 0.90$; in Fig. 10.4, $\Gamma = 0.80$), the upper (lower) abscissa for a given value of n represents the value of x/n that will be exceeded (fallen short of) with probability $(1 - \Gamma)/2$ in samples of size n from a binomial population with parameter P . A smooth curve was passed through the 11 points, but is shown on the chart only over the range $1/n' \leq x/n \leq 1 - 1/n'$, where n' is the next sample size above n shown on the chart. Outside this range the curve was bent so that at abscissas 0 and 1 the ordinates are $1 - (1 - \Gamma)^{1/n}$ and $(1 - \Gamma)^{1/n}$, respectively, instead of $1 - [(1 - \Gamma)/2]^{1/n}$ and $[(1 - \Gamma)/2]^{1/n}$. The reason for the difference in computation at $x/n = 0$ and 1 is that there the confidence interval must lie entirely to one side of the observed proportion. In deciding where to bend the curve, it was assumed that a given curve will never be used in the intervals $0 < x/n < 1/n'$ and $1 - 1/n' < x/n < 1$, and that only for interpolation will it ever be used in the intervals $1/n' < x/n < 1/n$ and $1 - 1/n < x/n < 1 - 1/n'$.

^{*} A slightly more accurate method is given in Chap. 1, Sec. 11.4.6, Problem II, where ϵ corresponds with $1 - \gamma$ of this chapter (see pp. 76-77).

characterize them as wasted and to try to keep n as small as possible. Actually these rounds supply information about the quality of the ammunition, and more information can easily result in an actual saving of ammunition. Suppose, for example, that a lot contains 10,000 rounds, of which (unknown to us) 10 (0.1 percent) are defective, that we wish to operate with a 0.99 confidence coefficient, and that the minimum tolerable probability of proofing a barrel is to be 0.99. Suppose further that in a sample of size 20 ($n = 20$) no defectives appear ($c = 0$). Proceeding as in Sec. 3.1, we construct the following table:

$n = 20$	$\gamma = 0.99$	$c = 0$
$\alpha = 0.01$	$r_1 = 2$	$r_2 = 40$
$x = 0.79433$	$\hat{p}_{0.99} = 0.20567$	
	Minimum	
N	probability	
1	0.79	
2	0.96	
3	0.99+	

Three rounds are needed for each barrel, so the total number of barrels proofed by the lot will be

$$\frac{10,000 - 20}{3} = 3,326 \quad (7)$$

Now, suppose that a sample of 60 ($n = 60$) had been taken and no defectives found. Then

$n = 60$	$\gamma = 0.99$	$c = 0$
$\alpha = 0.01$	$r_1 = 2$	$r_2 = 120$
$x = 0.92612$	$\hat{p}_{0.99} = 0.07388$	
	Minimum	
N	probability	
1	0.93	
2	0.99+	

Two rounds suffice for each barrel, and the total number of barrels proofed by the lot would be

$$\frac{10,000 - 60}{2} = 4,970 \quad (8)$$

a 49 percent increase over the previous result.

Of course the number of defectives in the sample of n is a chance variable whose distribution depends on n , among other parameters. On the basis of previous experience with the ammunition being used, it is possible to determine that value of n which is optimum in the sense that if the quality of the ammunition is essentially unchanged with time, the

This chapter was prepared by
Milton Friedman, University of Chicago

CHAPTER 11

PLANNING AN EXPERIMENT FOR ESTIMATING THE MEAN AND STANDARD DEVIATION OF A NORMAL DISTRIBUTION FROM OBSERVATIONS ON THE CUMULATIVE DISTRIBUTION

1. THE PROBLEM

A class of statistical problems of frequent occurrence arises from situations in which a characteristic is conceived to be normally distributed among the individuals of a population, but measurement of any one individual can show only whether the characteristic is above or below a certain level. The most familiar form of this problem concerns the lethality of varying doses of drugs. The electric impulse necessary to ignite a charge of powder in a certain system represents another such problem; for, although in this case it is possible to apply increasing impulses until ignition occurs, there is some evidence that an impulse that fails to cause ignition may alter the sensitivity of the system. In such situations a single stimulus of known intensity is applied to each individual. The resulting data show the proportions of the individuals tested at various intensities whose sensitivity fell *below* those intensities; in other words, the data for each level of stimulus intensity provide one observation on the cumulated distribution of sensitivities. These observations may be analyzed to estimate the mean and standard deviation of the sensitivity of the individuals comprising the population.

The present chapter is concerned with certain aspects of the planning of experiments that yield observations on the cumulated distribution and are analyzed to determine the mean and standard deviation of the distribution. For concreteness, the discussion is given in terms of the specific problem of planning an experiment to study the sensitivity of a radio proximity fuze. A radio proximity fuze, as its name suggests, makes use of radio waves to explode a projectile when and if it comes into proximity with a target; unlike time fuzes or point-detonating fuzes, it requires neither that a definite time of flight be set in advance nor that the target be hit directly. If proximity fuzes of a given model behaved identically there would, for fixed conditions, be a definite distance from the target within which all fuzes would operate and beyond which none would operate. Actually, there are random variations in the fuzes and in the impulses returned by the target; so if a number of fuzes pass exactly the same distance from a target under the same conditions, some operate

and some do not. An important parameter of fuze performance is, therefore, the probability that a fuze will operate if it passes within a certain distance of the target.

2. METHOD OF ANALYSIS

It has been determined from a certain set of 1,211 test firings made under relatively homogeneous conditions that the probability that a nondefective fuze will operate if it passes within a certain distance of the target can be well represented by assuming (a) that each nondefective fuze is characterized by a definite sensitivity, or maximum distance at which it will function, and (b) that these sensitivities are normally distributed among fuzes.

Let S be the sensitivity of a fuze, defined as the maximum distance at which that fuze fired under the given circumstances will function

μ be the true (population) arithmetic mean sensitivity

σ be the true (population) standard deviation of sensitivity

Then under the above assumptions the probability that a fuze will have a sensitivity between S and $S + dS$ is

$$\frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{(S-\mu)^2}{2\sigma^2}} dS \quad (1)$$

The proportion $T(d)$ of fuzes passing a given distance d from the target that operate is then the integral of (1) from d to ∞ , since every fuze whose sensitivity is greater than d will operate at d , while every fuze whose sensitivity is less will not. Therefore,

$$T(d) = \frac{1}{\sigma \sqrt{2\pi}} \int_d^{\infty} e^{-\frac{(S-\mu)^2}{2\sigma^2}} dS \quad (2)$$

In firing trials, it is not possible to observe the sensitivity of a fuze. Each fuze can be fired only once; all that can be observed is the minimum distance from the target and whether the fuze operated in proximity to the target.* The observations obtained are therefore observations on $T(d)$, the integral of the normal curve, and not directly on S .

Methods for analyzing such data have been developed, primarily in connection with dosage-mortality curves.† These methods involve writ-

* Actually, the entire trajectory of the fuze can be observed and also the actual point where the fuze operated. However, as these play no role in the problem considered here, they are ignored.

† See BLISS, "The Calculation of the Dosage-mortality Curve," "The Comparison of Dosage-mortality Data," "Estimating the Dosage-mortality Curve," and "The Calculation of the Time Mortality Curve"; also FISHER and YATES, *Tables*, pp. 8-12. (For full citations, see Sec. 6.)

ing (2) as

$$T(d) = \frac{1}{\sqrt{2\pi}} \int_Y^{\infty} e^{-\frac{z^2}{2}} dx \quad (3)$$

where

$$Y = \frac{d - \mu}{\sigma} \quad (4)$$

An observed value of $T(d)$ can be converted into an estimate of Y by means of tables of the normal probability integral.* The estimate of Y may be denoted by y . Now, Y is linearly related to d by

$$Y = -\frac{\mu}{\sigma} + \frac{1}{\sigma} d. \quad (5)$$

Hence the observed data may be analyzed by fitting a straight line to the observed values (y, d) . The usual direct methods of fitting a straight line cannot be used, however, since the variance of y is not a constant but depends on Y ; instead, a method of successive approximations is used. Tables are available to facilitate fitting the straight line by this method.† To avoid negative values, some of these tables use "probits," defined as normal deviates increased by 5, instead of the normal deviates themselves.

The function (5) was fitted to the data observed in the 1,211 test firings on fuze performance mentioned previously. The estimates of μ and σ turned out to be A and B , respectively.‡ Figure 11.1 shows the fitted function (5), as well as 90 percent confidence limits on it. These confidence limits were computed from the equation§

$$\sigma_y^2 = s_y^2 \left[\frac{1}{\sum_{i=1}^N w_i} + (d_i - \bar{d})^2 \frac{1}{\sum_{i=1}^N w_i (d_i - \bar{d})^2} \right] \quad (6)$$

where N = number of observed points to which the straight line was fitted

w_i = weight given to the i th point in getting the last approximation

\bar{d} = weighted average of observed values of d , that is,

$$\sum_{i=1}^N w_i d_i / \sum_{i=1}^N w_i$$

* For example, Table 1.5 in Chap. 1 of this volume.

† For example, FISHER and YATES, *Tables*, p. 49. Another useful set of tables is contained in Brown, *Tables to Facilitate the Analysis of Sensitivity Data*. This shows the ordinate Z of a normal curve, the probability P that a given normal deviate will be exceeded, $Q = 1 - P$, Z/PQ , and Z^2/PQ , all to 5 decimal places for values of Y from 0 to 3 by steps of 0.01.

‡ The numerical values of A and B , which cannot be published, are immaterial for the present purposes.

§ See BLISS, "The Calculation of the Dosage-mortality Curve."

s^2 = estimated variance of an observation about the last approximation, that is, if Y_i is the regression value for the i th point computed from the last approximation, then

$$s_v^2 = \frac{\sum_{i=1}^N w_i (y_i - Y_i)^2}{N - 2} \quad (7)$$

The problem then arose of collecting similar data under different conditions. Theoretical considerations gave little indication of the way in which the performance of the fuze would be affected by the difference

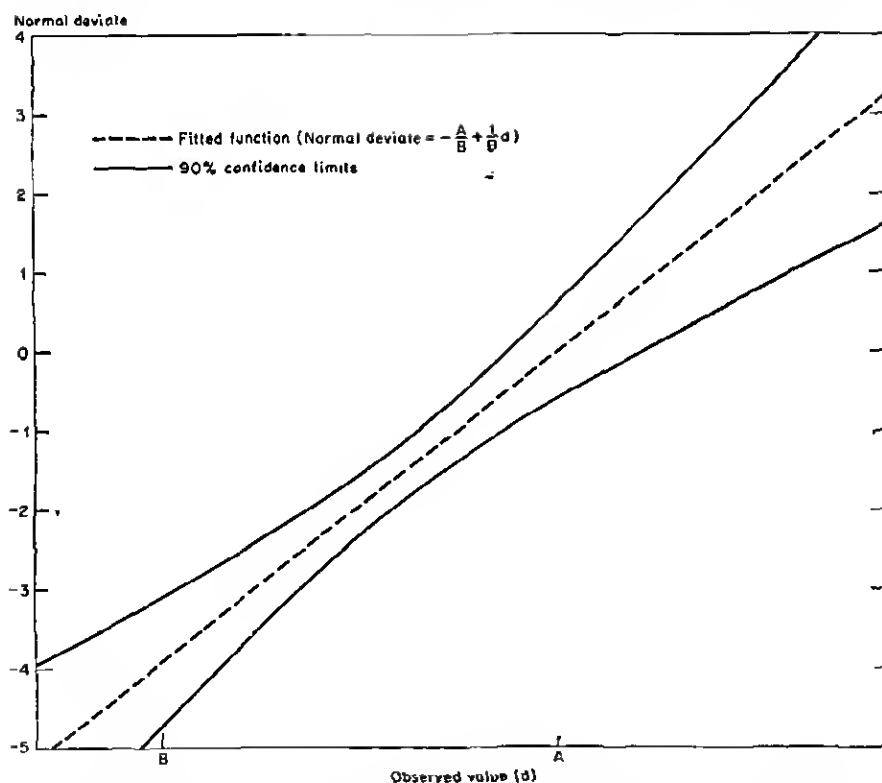


FIG. 11.1.—Fitted function with 90 percent confidence limits based on 1211 observations.

in conditions. The scale of the experiment had to be limited to at most 250 rounds. The statistical problem, with which the rest of this chapter deals, is that of distributing these rounds among various possible distances from the target in such a way as to get as accurate an estimate as possible of $T(d)$. This problem serves to illustrate a number of considerations

pertinent to such experiments; while no general, theoretical solution is offered, the mode of approach should be at least suggestive in similar situations.

3. STATISTICAL CONSIDERATIONS AFFECTING THE PLANNING OF THE EXPERIMENT

A paradox frequently arises in planning experiments. The most efficient design depends on the true value of the parameter under investigation, but if this were known there would be no need for the experiment. This paradox is usually evaded by basing the experimental design on some advance estimate of the parameters and trying to adjust the design so that the efficiency of the experiment is not much affected by minor differences between what is true and what is assumed. This method itself raises difficulties, for example, how much of the efficiency that the optimum design would have if the advance estimate were correct should be sacrificed to gain efficiency if the advance estimate is not correct?

This difficulty is present in marked degree in the problem under consideration and is aggravated by another difficulty, namely, that two parameters are to be estimated and the experimental design that is best for estimating one is not best for estimating the other. The two parameters to be estimated are μ and σ , or, what is equivalent, the slope and intercept of (5). The experiment would be most efficient if it could minimize both the variance of the estimate of μ and that of the estimate of σ ; unfortunately, the distribution of observations that minimizes the variance of the estimate of μ is decidedly different from that which minimizes the variance of the estimate of σ .

If σ were known, the variance of the estimate of μ would be minimized by taking all observations at a single distance equal to μ . But since σ is not known, it would be self-defeating to take all observations at a single distance, because (a) this would make it impossible to correct the advance estimate of μ , and (b) it would give no information at all about σ . If the observed value of $T(d)$ were 50 percent, the estimate of μ from the experiment would be equal to the value of d at which the firings were made, that is, it would be the same as the advance estimate. If the observed value of $T(d)$ were other than 50 percent, the experiment would indicate that the advance estimate of μ was wrong but no new estimate could be made. Only one point on the straight line (5) would be available, so its slope could not be estimated; hence, it would be impossible to estimate the value of d at which $T(d) = 50$ percent. These statements are equivalent, of course, to saying that no estimate of σ would be possible either. The most that could be learned from an experiment with all observations at an estimated μ would be whether this estimate was correct.

The variance of the estimate of σ would be minimized by taking all observations at two values of d , approximately 1.6 times the estimated

value of σ on either side of the estimated value of μ . Even though this would not give as accurate an estimate of μ as could be obtained by placing the observations closer to μ , it is a workable arrangement in that it would yield estimates of both μ and σ even though the advance estimates were in error.

From these considerations alone, the appropriate compromise would appear to be to place the observations in two groups located symmetrically about the estimated μ but closer to it than the distance that would minimize the variance of the estimate of σ . To decide how much closer would require deciding how much it is worth sacrificing accuracy in σ to gain accuracy in μ .

Other considerations must, however, be taken into account. Placing all the observations at two points puts great reliance on the validity of equation (2) as a description of $T(d)$. This relation was derived from a single body of data, for which its validity cannot be considered conclusively established; it may, therefore, not be valid for the new experiment. Observations at only two values of d cannot, however, show whether it is valid or not, since there will be only two points to which to fit (5), and a straight line can always be fitted perfectly to two points. In order to determine whether (2), and hence (5), describe the data reasonably well, it is necessary to spread the observations among more values of d . The desirability of spreading the observations was reinforced in the present experiment by the fact that the data were to be used for other purposes, in particular, to study the location of points of functioning, for which a wide spread seemed desirable.

Other considerations to be taken into account in the particular experiment were (1) it was not feasible to use distances greater than about $A + \frac{5}{3}B$; (2) most of the firings in the earlier experiment had been at short distances, so that it seemed desirable to have some firings in the new experiment at short distances in order to make a direct comparison of the results of the two experiments, independent of any assumptions about the form of $T(d)$.

4. POSSIBLE DESIGNS

In the light of the preceding considerations, five alternative distributions of 250 observations were considered. These are shown in Table 11.1.

Plans 1 and 2 are suggested by considering how to minimize the variance of the estimate of σ . The advance estimates, based on the previous experiment, were A for μ and B for σ . The 250 observations in Plans 1 and 2 are divided into two groups and placed symmetrically on either side of the mean. In Plan 2, they are about as far apart as is required to minimize the estimate of σ ; in Plan 1, they are brought closer

together to get a more accurate estimate of μ . Plan 3 spreads the observation evenly over the five classes spanned by Plan 2; it is symmetrical, and its largest distance is the largest that is feasible. Plans 4 and 5 are attempts to get some data for the short distances for comparison with the previous experiment. In Plan 4, the observations for the low distances are obtained by omitting those at A , since if A is the true mean, such firings give no information about σ . In Plan 5, the observations for the low distances are taken equally from the five groups in Plan 3.

To measure the relative efficiency of these five possible designs, 90 per cent confidence limits on (5) were computed for each, assuming that the correct straight line was that obtained in the earlier experiment,

$$Y = -\frac{A}{B} + \frac{1}{B}d \quad (8)$$

The confidence limits for Plans 1 and 2 are plotted in Fig. 11.2, together with the confidence limits obtained from the earlier experiment (shown also in Fig. 11.1).^{*} Table 11.2 shows these confidence limits and the assumed correct values in somewhat different form, namely, in terms of 100 $T(d)$, the percentage of nondefective fuzes.

TABLE 11.1
ALTERNATIVE DISTRIBUTIONS OF 250 OBSERVATIONS

Distance	Number of rounds to be fired under plan				
	1	2	3	4	5
$A - 2\frac{1}{2}\%B$				20	20
$A - 1\frac{1}{2}\%B$				30	30
$A - 1\%B$		125	50	50	40
$A - \frac{1}{2}\%B$	125		50	50	40
A			50		40
$A + \frac{1}{2}\%B$	125		50	50	40
$A + 1\%B$		125	50	50	40

Two points are fairly clear from Fig. 11.2 and Table 11.2 (1) Any of the five plans for 250 observations gives as much information as, if not somewhat more than, the 1,211 observations used in the earlier experiment; (2) the five possible plans do not differ substantially in efficiency. Plan 1, which emphasizes most strongly the accuracy of the estimate of μ , gives therefore the narrowest confidence limits for distances near the mean. Plan 2, which emphasizes most the accuracy of the estimate of σ , gives the narrowest limits for distances far from the mean but the widest

^{*} The confidence limits for Plans 3, 4, and 5 are omitted from Fig. 11.2 only because they are so close to those for Plans 1 and 2 that if all five were plotted on a figure the size of Fig. 11.2, it would be impossible to distinguish the five lines.

TABLE 11.2
NINETY PERCENT CONFIDENCE LIMITS ON ASSUMED FUNCTION FOR FIVE ALTERNATIVE PLANS FOR 250 OBSERVATIONS
(In percent of nondefective fuzes operating)

Distance, d	Assumed function	90% confidence limits for plan										90% confidence limits from earlier data.	
		1		2		3		4		5			
		Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
$A - 2\frac{1}{2}\%B$	100.0	99.7	100.0	99.9	100.0	99.8	100.0	90.8	100.0	99.7	100.0	99.9	100.0
$A - 2\%B$	99.9	98.6	100.0	99.2	100.0	98.8	100.0	99.0	100.0	98.7	100.0	99.6	100.0
$A - 1\frac{1}{2}\%B$	99.3	94.9	99.9	90.1	99.9	05.3	99.9	95.6	99.9	95.1	99.9	97.7	99.8
$A - 1\%B$	95.0	85.7	98.7	86.5	98.5	86.1	98.6	86.2	98.6	85.6	98.7	90.2	97.7
$A - \frac{1}{2}\%B$	70.7	68.0	88.4	65.8	89.5	67.8	88.5	66.9	89.0	67.0	88.9	65.8	89.5
A	50.8	40.7	60.9	36.1	65.4	39.8	61.8	37.8	63.7	38.7	62.9	27.7	73.7
$A + \frac{1}{2}\%B$	21.5	12.5	33.4	11.4	35.4	12.4	33.6	11.6	35.1	11.6	35.0	5.1	52.2
$A + 1\%B$	5.5	1.5	15.2	1.7	14.1	1.6	14.7	1.5	15.2	1.4	15.8	0.4	30.5
$A + 1\frac{1}{2}\%B$	0.8	0.1	5.4	0.1	4.1	0.1	5.0	0.1	5.0	0.1	5.6	0.0	14.3
$A + 2\%B$	0.1	0.0	1.5	0.0	0.8	0.0	1.3	0.0	1.2	0.0	1.5	0.0	5.2

limits for distances near the mean. The other plans are in general intermediate.

On the basis of this evidence, it was decided to recommend Plan 5. This plan covers the largest number of values of d and therefore comes closest to satisfying objectives other than the minimization of the variance of estimates of μ and σ ; at the same time, it does not sacrifice much efficiency in the estimation of μ and of σ .

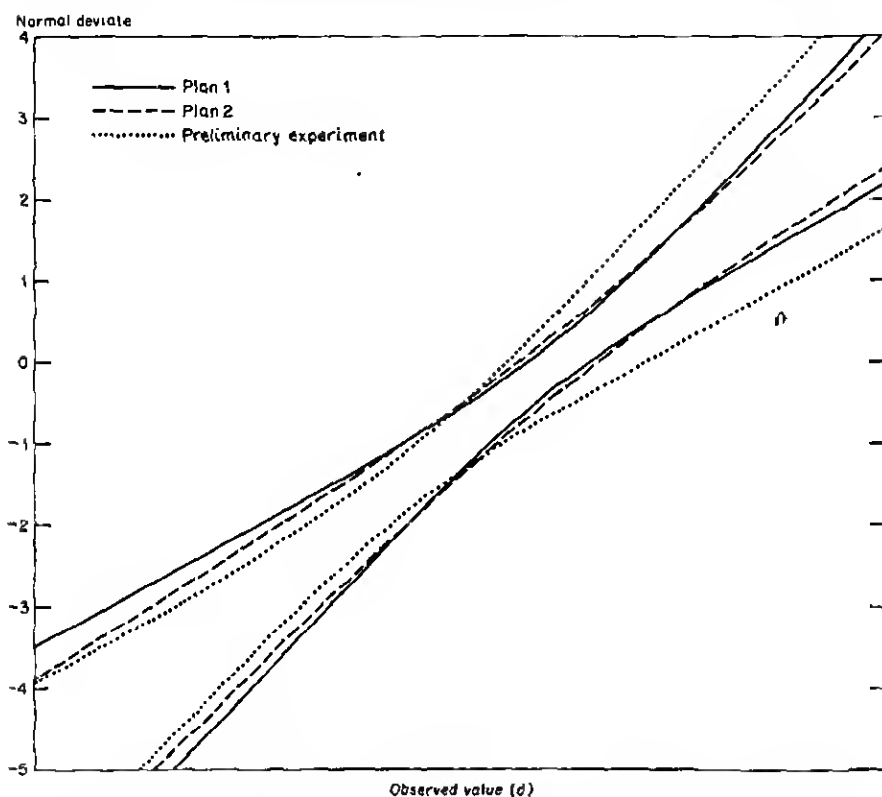


FIG. 11.2.—Ninety percent confidence limits on assumed function for two experimental designs utilizing 250 observations, and for preliminary experiment based on 1211 observations.

5. TECHNICAL NOTES*

The problem of determining the optimum distribution of observations for estimating μ and σ is considerably simplified by the following two requirements, which seem plausible and will be accepted here without rigorous proof:

* This section presumes a knowledge of the methods of analyzing probit data (see References, Sec. 6).

(1) The symmetry of the normal distribution implies that the optimum distribution of observations will be symmetrical about the true mean μ . Note that replacing $d - \mu$ by its negative will have no effect on variances, since these involve only (a) the weights, which depend only on the absolute value of $(d - \mu)/\sigma$, and (b) the squares of quantities like $d - \mu$.

(2) Since the problem is one of fitting a straight line containing two parameters, the optimum distribution will involve placing all the observations at two values of d . These two values of d enter into the variances in the form of linear combinations of weighted squared deviations. If one pair of values, d_1 and d_2 , such that $d_1 - \mu = -(d_2 - \mu)$, contributes more to the minimization of the variance than another pair of values, say d_3 and d_4 , such that $d_3 - \mu = -(d_4 - \mu)$, it will continue to do so no matter how many observations are shifted from d_3 and d_4 to d_1 and d_2 .

These two assumptions reduce the problem to one of determining a pair of values d_1 and d_2 such that $d_1 - \mu = -(d_2 - \mu)$, at each of which half the observations are to be placed.

Let μ = population mean

σ = population standard deviation

m = estimate of μ

s = estimate of σ

$$Y_i = \frac{d_i - \mu}{\sigma} \quad (i = 1, 2)$$

$$y_i = \frac{d_i - m}{s} = \text{estimate of } Y_i$$

$$T_i = \frac{1}{\sqrt{2\pi}} \int_{Y_i}^{\infty} e^{-\frac{x^2}{2}} dx = \text{true proportion above } d_i$$

t_i = estimate of T_i

Observed values of t_i give, from tables of probits or of the normal distribution, estimates of y_i , and hence two equations

$$y_1 = \frac{d_1 - m}{s} \tag{9}$$

$$y_2 = \frac{d_2 - m}{s} \tag{10}$$

Solving for m and s gives

$$m = \frac{y_1 d_2 - y_2 d_1}{y_1 - y_2} \tag{11}$$

$$s = \frac{d_1 - d_2}{y_1 - y_2} \tag{12}$$

It is known* that

$$\sigma_{y_i}^2 = \frac{T_i(1 - T_i)}{n_1 z_i^2} \tag{13}$$

where

* See BLISS, "The Calculation of the Dosage-mortality Curve."

n_i = number of observations at d_i

$$z_i = \frac{1}{\sqrt{2\pi}} e^{-\frac{Y_i^2}{2}}$$

To a first approximation,

$$\sigma_m^2 = \left(\frac{\partial m}{\partial y_1} \right)_{y_1=y_2}^2 \sigma_{y_1}^2 + \left(\frac{\partial m}{\partial y_2} \right)_{y_1=y_2}^2 \sigma_{y_2}^2 \quad (14)$$

$$\sigma_s^2 = \left(\frac{\partial s}{\partial y_1} \right)_{y_1=y_2}^2 \sigma_{y_1}^2 + \left(\frac{\partial s}{\partial y_2} \right)_{y_1=y_2}^2 \sigma_{y_2}^2 \quad (15)$$

The partial derivatives in (14) and (15) may be evaluated as follows:

$$\frac{\partial m}{\partial y_1} = \frac{y_2(d_1 - d_2)}{(y_1 - y_2)^2} \quad (16)$$

$$\frac{\partial m}{\partial y_2} = \frac{-y_1(d_1 - d_2)}{(y_1 - y_2)^2} \quad (17)$$

$$\frac{\partial s}{\partial y_1} = \frac{-(d_1 - d_2)}{(y_1 - y_2)^2} \quad (18)$$

$$\frac{\partial s}{\partial y_2} = \frac{d_1 - d_2}{(y_1 - y_2)^2} \quad (19)$$

Hence

$$\sigma_m^2 = \frac{Y_1^2(d_1 - d_2)^2}{(Y_1 - Y_2)^4} \frac{T_1(1 - T_1)}{n_1 z_1^2} + \frac{Y_2^2(d_1 - d_2)^2}{(Y_1 - Y_2)^4} \frac{T_2(1 - T_2)}{n_2 z_2^2} \quad (20)$$

$$\sigma_s^2 = \frac{(d_1 - d_2)^2}{(Y_1 - Y_2)^4} \frac{T_1(1 - T_1)}{n_1 z_1^2} + \frac{(d_1 - d_2)^2}{(Y_1 - Y_2)^4} \frac{T_2(1 - T_2)}{n_2 z_2^2} \quad (21)$$

Substituting for Y_1 and Y_2 in (20) and (21) and simplifying gives

$$\sigma_m^2 = \frac{\sigma^2}{(d_1 - d_2)^2} \left[(d_2 - \mu)^2 \frac{T_1(1 - T_1)}{n_1 z_1^2} + (d_1 - \mu)^2 \frac{T_2(1 - T_2)}{n_2 z_2^2} \right] \quad (22)$$

$$\sigma_s^2 = \frac{\sigma^4}{(d_1 - d_2)^2} \left[\frac{T_1(1 - T_1)}{n_1 z_1^2} + \frac{T_2(1 - T_2)}{n_2 z_2^2} \right] \quad (23)$$

So far, no use has been made of the symmetry requirement. Equations (22) and (23) are therefore valid for any pair of values of d_1 and d_2 . Symmetry implies that

$$n_1 = n_2 \quad (24)$$

$$(d_1 - \mu) = -(d_2 - \mu) \quad (25)$$

$$T_1 = 1 - T_2 \quad (26)$$

$$z_1 = z_2 \quad (27)$$

From (25),

$$d_1 - d_2 = 2(d_1 - \mu) \quad (28)$$

Substituting into (22) and (23) gives

$$\sigma_m^2 = \frac{\sigma^2}{2} \frac{T_1(1 - T_1)}{n_1 z_1^2} \quad (29)$$

$$\sigma_s^2 = \frac{\sigma^4}{2(d_1 - \mu)^2} \frac{T_1(1 - T_1)}{n_1 z_1^2} = \frac{\sigma^2}{2Y_1^2} \frac{T_1(1 - T_1)}{n_1 z_1^2} \quad (30)$$

σ_m^2 will be a minimum if $T_1(1 - T_1)/z_1^2$ is a minimum with respect to d_1 or, what is the same thing, with respect to Y_1 . But $T_1(1 - T_1)/z_1^2$ is a minimum at $Y_1 = 0$, as can be demonstrated by differentiating or, more simply, by a glance at the tabled values of $z_1^2/T_1(1 - T_1)$.^{*} Hence, to minimize the variance of m , with σ assumed known, it would be necessary to put all the observations at μ .

σ_s^2 will be a minimum if $T_1(1 - T_1)/z_1^2 Y_1^2$ is a minimum. Differentiating yields an equation that would have to be solved numerically. Since, as noted above, $z_1^2/[T_1(1 - T_1)]$ is tabled, it is simpler to compute directly $Y_1^2 z_1^2/[T_1(1 - T_1)]$ and determine numerically the value of Y_1 at which it reaches a maximum. This gives approximately 1.574 or 1.575 as the value of Y for which σ_s^2 is a minimum.[†] Hence, the variance of s will be minimized by putting half the observations at $d_1 = \mu + 1.57\sigma$, and half at $d_2 = \mu - 1.57\sigma$.

6. REFERENCES

- BLISS, C. I.: "The Calculation of the Dosage-mortality Curve," *Annals of Applied Biology*, Vol. 22 (1935), pp. 134-167.
 ———: "The Comparison of Dosage-mortality Data," *Annals of Applied Biology*, Vol. 22 (1935), pp. 307-333.
 ———: "Estimating the Dosage-mortality Curve," *Journal of Economic Entomology*, Vol. 28 (1935).
 ———: "The Calculation of the Time Mortality Curve," *Annals of Applied Biology*, Vol. 24 (1937), pp. 815-852.
 BROWN, RICHARD H.: *Tables to Facilitate the Analysis of Sensitivity Data*, NavOrd Report No. 205-45, Bureau of Ordnance, Navy Department, Washington, D.C., September 5, 1945, 15 pp.
 FISHER, RONALD A., and YATES, FRANK: *Statistical Tables for Biological, Agricultural and Medical Research*, 2d ed., Oliver and Boyd, Ltd., London and Edinburgh, 1943, 98 + viii pp.

^{*} See Fisher and Yates, *Tables*, Table XI, where what is designated here $z_1^2/[T_1(1 - T_1)]$ is designated Z^2/PQ . A table for finer intervals of Y is available from the Division of Pharmacology, Food and Drug Administration, United States Department of Agriculture, Washington 25, D.C.

[†] The computed values of $Y_1^2 z_1^2/[T_1(1 - T_1)]$ for a few values in the neighborhood of the maximum are, when diminished by 0.608 and multiplied by 10^4

Y_1	1.55	1.56	1.57	1.58	1.59
$\frac{Y_1^2 z_1^2}{T_1(1 - T_1)}$	7	30	41	40	29

CHAPTER 12

ABANDONING AN EXPERIMENT PRIOR TO COMPLETION

	PAGE
1. Introduction	355
1.1 Nature of the Problem	355
1.2 Given Features of the Experiment	356
1.3 Statistical Problem	356
2. Proposed Solution	357
2.1 Approximating the Rejection Line by Sequential Principles.	357
2.2 Adjusting the Rejection Line to Take Account of the Acceptance Line.	358
3. An Example.	359
4. Calculation of OC Curve	361
5. References.	362

This chapter was prepared by the editors.

The idea is due to L. J. Savage, University of Chicago, and the techniques are due to Kenneth J. Arnold, University of Wisconsin, and M. A. Girshick, U.S. Bureau of the Census

CHAPTER 12

ABANDONING AN EXPERIMENT PRIOR TO COMPLETION

1. INTRODUCTION

Every experiment is designed in the light of certain presumptions about the underlying phenomena to be studied, if only the presumption that the phenomena warrant study. It is not always possible, however, to confirm these presumptions in advance. In such cases it may be desirable to introduce a sequential element into the design of the experiment so that the experimental program can be adjusted to any facts about the basic assumptions disclosed during the course of the investigation. The present chapter considers a simple design of this type, where an experiment is to be undertaken to estimate a parameter of a continuous distribution, but provision is to be made to abandon the experiment prior to completion if the accumulated evidence at any stage reveals that the underlying population does not warrant study.

1.1. Nature of the Problem

The circumstances giving rise to the need of an experiment that provides for possible abandonment are these: A new mechanism has been constructed whose performance, in functioning models, is thought to be superior to that of similar standard mechanisms. It is accordingly desired to determine the average and variability of a particular performance characteristic from an experiment of sufficient size to give reliable estimates of these parameters. There is reason to fear, however, that the proportion of breakdowns may be prohibitively high, in which case the mechanism cannot be used in its present state of development and the estimation of its performance parameters is of little value. Moreover, because the experiment will be costly in time, personnel, and equipment, considerable saving will result from discontinuing the experiment at an early stage if the mechanism exhibits too high a failure rate. An experiment is therefore desired that incorporates the following provisions: (1) If the failure rate exceeds a certain tolerance standard, there must be a preassigned degree of assurance of rejecting the mechanism and terminating the experiment; (2) if the failure rate is below a certain acceptable standard, there must be a preassigned degree of assurance of completing the experiment; (3) the experiment should cease at the earliest point at which the accumulated evidence is sufficient to reject the mechanism with the required degree of assurance.

1.2. Given Features of the Experiment

Previous investigation of the mechanism appears to justify the assumption that the performance characteristic under study is normally distributed about some unknown average value. Moreover, from provisional figures it appears that a satisfactory balance between the cost of the experiment and the precision of the estimates can be obtained by a $2 \times 2 \times 2 \times 2$ factorial experiment involving duplicate observations, that is, from 32 observations. Certain details of the experiment can thus be specified at once. If the mechanism has an acceptable failure rate, no fewer than 32 items can be tested, since 32 measurements of performance are required; on the other hand, no more than 32 *functioning* items need be examined, since these will yield the required number of measurements for estimation with the minimum amount of testing. Thus the criterion for accepting the mechanism can be represented graphically as a straight line by plotting the number of items that fail against the number of items tested. This acceptance line intersects the base line at 32, showing that no fewer than 32 items can be tested; it has a slope of 1, showing that if failures occur, the number of items tested shall be only sufficient to yield 32 performance measurements. As the experiment proceeds, a point can be plotted after each test representing the cumulated number of failures and the number of tests made; when such a point reaches the acceptance line the experiment is complete, for 32 performance measurements have been obtained.

1.3. Statistical Problem

If several hundred trials are made without obtaining the 32 performance measurements needed to complete the experiment, it is obvious that the failure rate is excessive and the experiment ought to be abandoned. This suggests the advisability of introducing a rejection line, showing for each number of items tested the number of failures that would justify rejecting the mechanism and abandoning the experiment; the rejection line should intersect the vertical axis above 0 and have a slope less than 1. The two lines together yield a closed region such that, if the point representing the number of failures and the number of items tested crosses the upper line, the mechanism is rejected and the experiment abandoned; while if the point crosses the lower line, the mechanism is accepted and estimates are made from the resulting 32 measurements.

Since the lower line is fixed by the conditions of the problem, the statistical problem that remains is clearly to determine the upper line in such a way as to meet preassigned requirements on the probabilities of abandonment and completion, with a minimum average amount of testing. No general solution to this problem has been found. The following

discussion will show, however, that sequential principles* can be used to give a good approximation to the solution.

To formulate the problem more precisely, we assume that a proportion of failures p_2 exists that is considered unacceptable; that is, if the failure rate equals or exceeds p_2 , we wish to reject the mechanism. If the failure rate is less than p_2 , however, we are willing to accept the mechanism; and in particular, if it is less than some value p_1 , we wish a high degree of assurance of accepting the mechanism.

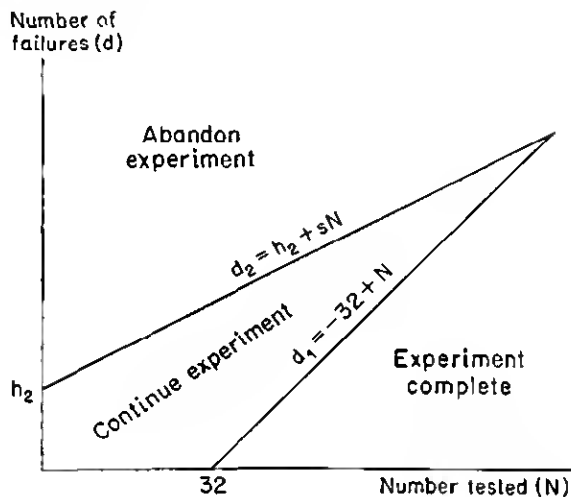


FIG. 12.1.

2. PROPOSED SOLUTION

2.1. Approximating the Rejection Line by Sequential Principles

The use of sequential principles to meet these requirements is suggested by the desire to minimize the necessary amount of sampling. A sequential criterion makes it possible to reappraise the failure rate of the mechanism after each test and to determine on the basis of the accumulated evidence whether (a) to reject the mechanism, (b) to accept it, or (c) to continue the experiment. As soon as the accumulated evidence is sufficient for decision (a) or (b), the experiment stops and further, unnecessary experimenting is avoided. The usual sequential test, however, consists of both an acceptance criterion and a rejection criterion, whereas completion of the test under consideration requires only a rejection criterion. What we seek, therefore, is a sequential test which makes no provision for acceptance but which achieves certain assigned probabilities of rejection for the specified failure rates p_1 and p_2 . Having found such a test, we can provide for actual acceptance by combining

* See Chap. 17 for a brief account of sequential analysis.

our sequential rejection criterion with the predetermined acceptance criterion, taking care to allow for the effect of this combination on the total probabilities of rejection.

The desired sequential rejection criterion can be derived as a special case of the ordinary sequential binomial test. The ordinary test can be represented on a chart similar to Fig. 12.1 by a pair of parallel straight lines having a slope s and intercepts $-h_1$ and h_2 . A sequential test which provides only for rejection, that is, which consists solely of the upper decision line, may be regarded as a limiting case of an ordinary sequential binomial test with $h_1 = \infty$. This conception enables us to use the formulas for the usual two-decision test to obtain the operating-characteristic (OC) curve of a one-decision sequential test, that is, the probability of acceptance L_p as a function of the true population proportion of failures p . When $h_1 = \infty$, the OC curve is given by*

$$p = \frac{R_p^{-\frac{s}{h_2}} - 1}{R_p^{-\frac{1}{h_2}} - 1} \quad \text{when } p \leq s \quad (1)$$

and by

$$R_p = 1 - L_p = 1 \quad \text{when } p > s \quad (2)$$

Thus, the probability of rejecting is 1 if $p > s$; it lies between 0 and 1 if $p \leq s$. Accordingly, we take the value p_2 , representing the failure rate above which we want to abandon the experiment, as the slope s of the one-decision sequential test. Then if α is the risk we are willing to run of abandoning the experiment and rejecting the mechanism when the true failure rate is only p_1 , we may substitute p_1 for p , α for R_p , and p_2 for s in equation (1) and solve for h_2 .†

2.2. Adjusting the Rejection Line to Take Account of the Acceptance Line

Having determined the one-decision sequential test that yields the requisite probabilities of rejection, we now take into account the acceptance criterion resulting from the conditions of the experiment. This acceptance criterion affects the probabilities in two respects. (1) The probabilities of rejection will be decreased, since those samples which

* See Statistical Research Group, *Sequential Analysis*, Appendix B, equations (B.80) and (B.81). (For full citations, see Sec. 5.)

† An approximation to h_2 can be obtained by replacing p_2 of the formula

$$h_2 = \frac{\log \frac{1}{\alpha}}{\log \frac{p_2}{p_1} \left(\frac{1 - p_1}{1 - p_2} \right)}$$

(*Sequential Analysis*, Sec. 2, equation 2.204) by $p_2 + (p_2 - p_1) = 2p_2 - p_1$.

would lead to late rejection will not be rejected at all (in fact, will now be accepted); (2) for every value of $p < 1$, whether or not $p > s$, the probability of acceptance will be greater than zero. The net effect of the acceptance line is thus to increase the chances of acceptance for all values of $p < 1$. This means that L_{p_2} ($= 1 - R_{p_2}$) will now be positive; while R_{p_1} will be less than α . The decrease in R_{p_1} is, of course, desirable, but it can be attained only at the cost of additional testing beyond that necessary to maintain R_{p_1} at the required level α . It remains therefore to readjust the decision lines so that R_{p_1} will be α and L_{p_1} will be at an acceptably low level, say β .

Since the acceptance line is fixed by the conditions of the problem, the necessary changes in the decision lines must be made entirely in the rejection line. It is apparent that the probabilities of rejection can be increased either by reducing h_2 or by reducing s , or both. It is not clear, however, what combination of adjustments will give the desired risks α and β with a minimum amount of inspection. We therefore resort to trial and error to find a combination of h_2 and s that gives the desired probabilities of acceptance, leaving unsettled the question whether this combination of h_2 and s is the best possible from the standpoint of the average amount of testing. Fortunately, this trial-and-error process can be carried out without too much difficulty, for a straightforward method exists for computing the OC curve for any binomial test of the sort here described. Thus, by determining the OC curve corresponding to each of a number of combinations of h_2 and s , that combination can be chosen which gives the requisite probabilities of acceptance at p_1 and p_2 . This procedure will yield a plan for the experiment which, though probably not optimum from the standpoint of minimizing inspection, will serve as an approximation to the type of plan desired, that is, lead to early abandonment of the experiment if the true failure rate is high; moreover, the OC curve will be available, so the consequences of using the plan will be fully known.

3. AN EXAMPLE

To illustrate the method of solution outlined in Sec. 2, let us suppose that if as many as half the mechanisms are failures we wish a high degree of assurance of abandoning the experiment and rejecting the proposed model, if as few as 40 percent are failures we wish a high degree of assurance of completing the experiment. Let the desired probability of completing the experiment if the failure rate is as high as 50 percent be $\beta = 0.10$, and the probability of abandoning the experiment if the failure rate is as low as 40 percent be $\alpha = 0.10$.

The lower, or acceptance line is determined by the requirements for estimating the performance parameters, as explained above; its equation

is

$$d_1 = -32 + N \quad (3)$$

where d_1 represents the cumulated number of failures and N represents the number of tests made.

The first approximation to the rejection line is given by the one-decision sequential test for which $s = 0.5$ and h_2 is obtained from

$$0.4 = \frac{0.1^{-\frac{0.5}{h_2}} - 1}{0.1^{-\frac{1}{h_2}} - 1} \quad (4)$$

Writing

$$x = 0.1^{-\frac{1}{h_2}} \quad (5)$$

we have

$$0.4 = \frac{x^{0.5} - 1}{x - 1} = \frac{1}{x^{0.5} + 1} \quad (6)$$

$$x^{0.5} = 1.5 \quad (7)$$

$$x = 2.25 \quad (8)$$

Then, from (5),

$$\begin{aligned} h_2 &= \frac{-\log 0.1}{\log x} \\ &= \frac{1}{\log 2.25} \\ &= 2.84 \end{aligned} \quad (9)$$

A moment's reflection on the orientation of the line $d_2 = 2.84 + 0.5N$ on the graph relating number of failures to number of items tested shows that so long as $s = 0.5$, all values of h satisfying the inequality $2.5 < h \leq 3$ are equivalent, since observed values of d and N must be integers. In view of this, and because we expect this first approximation to yield too large probabilities of acceptance, we place the initial value of h_2 at 2.5. The first approximation to our test is thus defined by the two straight lines with equations

$$d_2 = 2.5 + 0.5N \quad (\text{rejection line}) \quad (10)$$

$$d_1 = -32 + N \quad (\text{acceptance line}) \quad (11)$$

However, this combination fails to give a satisfactory OC curve, the values of L_p being excessive throughout the range of p . On the other hand, the combination $h_2 = 1.6$ and $s = 0.4$ gives values of L_p that are too small, and so also do the combinations $h_2 = 1.5$, $s = 0.5$ and $h_2 = 2.2$, $s = 0.4$. A fifth set, $h_2 = 2.5$ and $s = 0.4$, gives the following OC curve, which, though departing from that originally specified, appears satisfactory.

Proportion of failures	Probability of completing experiment
0.1	1.000—
0.2	0.990
0.3	0.904
0.4	0.532
0.5	0.102
0.6	0.003

4. CALCULATION OF OC CURVE

The method of calculating the OC curve for any particular experimental plan of the type described is discussed at length elsewhere,* so it will be outlined here only in general terms.

The basis of the method is the fact that in any truncated sequential test, the number of possible outcomes in sampling is finite and, in practical cases, fairly small. It is therefore possible to enumerate all possible outcomes of the test and to determine the total probability of those outcomes which lead to acceptance, that is, the value of L_p .

This calculation is accomplished step by step, as follows: For the first stage of the experiment, all possible ways in which the sample might turn out are specified, and the probability of each outcome is computed on the assumption that the true failure rate of the mechanism is some particular value, say p_1 . These outcomes are then classified into two groups, those which lead to acceptance and those which lead to the decision to continue testing. The sum of the probabilities of the first class gives the total probability of acceptance at the first stage of the experiment. Each outcome in the second class is then considered as a possible point of departure for the next stage of the experiment; and for each such point of departure, the possible outcomes of the second stage are considered and classified as before. The sum, over all points of departure, of the probabilities of those outcomes which lead to acceptance at the second stage then gives the total probability of acceptance at stage two, while the sum of such probabilities over both stages gives the total probability of acceptance for the first two stages. This basic method of calculation can be carried through the remaining (finite number of) stages of the experiment.

The total probability of acceptance taken over all stages represents the probability L_p , that the experiment will lead to acceptance when the true failure rate is p_1 . By systematic methods these calculations can be duplicated for a choice of different values of p , so that a sequence of values of p and L_p sufficient to determine the entire OC curve, or at least those points of principal interest on the OC curve, can be determined. It is in this fashion that the points on the OC curve in Sec. 3 were determined.

* Statistical Research Group, *Sampling Inspection*, Chap. 17, Sec. 2, pp. 187-202.

This method of attack yields only one of many possible tests of the sort described, all having the same probabilities $L_{p_1} = 0.90$ and $L_{p_2} = 0.10$. The optimum test may thus be viewed as the particular one of these tests which requires the smallest average amount of inspection for the relevant range of p . By sufficient calculation this test might be determined by trial and error, since the probabilities used to determine the OC curve of a test suffice to calculate the curve representing the average amount of sampling as a function of the failure rate p (the ASN curve).^{*} If, therefore, we were to determine a whole class of tests with the same L_{p_1} and L_{p_2} , we could choose that one whose ASN curve showed the least average cost in sampling in the relevant range of p . However, the volume of calculation necessary to use this approach renders it impractical.

5. REFERENCES

- Statistical Research Group, Columbia University: *Sampling Inspection*, McGraw-Hill Book Company, Inc., New York, 1947.
———: *Sequential Analysis of Statistical Data: Applications*, rev. ed., Columbia University Press, New York, 1945.

^{*} For a method of calculating the ASN curve in such cases, see Statistical Research Group, *Sampling Inspection*, Chap. 17, Sec. 3.2, pp. 203-209.

CHAPTER 13

PLANNING EXPERIMENTS SEEKING MAXIMA

	PAGE
1. Type of Problem.	365
2. Purposes of Experiment.	365
3. Deficiencies of Factorial Design	366
4. A Sequential Design	367
5. Comparison of Factorial and Sequential Designs	369
5.1 Number of Observations.	369
5.2 Time Trends.	371
6. References.	372

This chapter was prepared by
Milton Friedman, University of Chicago
L. J. Savage, University of Chicago

CHAPTER 13

PLANNING EXPERIMENTS SEEKING MAXIMA

1. TYPE OF PROBLEM

This chapter deals almost entirely with a special class of experiments, namely, those designed to determine the conditions for which some function attains a maximum. For example, experiments may be conducted on the breaking strength of a type of alloy to determine the composition producing maximum strength. It is not the primary object of such experiments to determine the functional relation between strength and composition, nor even to measure the strength, maximum or otherwise; the primary object is to find a particular combination of the independent variables at which the maximum of the dependent variable is nearly attained. Although the planning of experiments has become a major branch of statistics, little attention has been given to this important class of problem, which is especially common in engineering and development work.*

For concreteness, this chapter considers the specific problem of planning a metallurgical experiment to find the best composition of a certain type of alloy for maximizing the time to rupture under a given stress at a given elevated temperature. Clearly, the principles elucidated in terms of this particular problem are applicable to a wide class of problems.

2. PURPOSES OF EXPERIMENT

The problem considered is one in which a single observable result (number of hours it takes a specimen to rupture) is a function of many independent variables (method of treating the alloy, chemical composition of the alloy, and so forth). An experiment is to be conducted in which the result is to be measured for a series of values of the independent variables.

Such an experiment is likely to have two somewhat different purposes: (1) To find the values of the independent variables that make the function (that is, the observable result) a maximum; (2) to evaluate the function in the neighborhood of the maximum. At the present stage of metallurgical knowledge, finding the maximum is usually the primary purpose. There is reason to believe that nothing like the maximum

* The pathbreaking work on the problem is that of Hotelling, "Experimental Determination of the Maximum of a Function." (For full citations, see Sec. 6.)

possible strength has yet been attained; and the theory of the subject is so undeveloped as to make direct experiment the most fruitful approach toward finding stronger alloys. Moreover, there is relatively little interest in knowing the behavior of the function in regions rather distant from the maximum.

If the function has more than one maximum, the ultimate objective is to find the largest maximum—the absolute maximum. In general, however, this objective is unattainable without complete knowledge of the entire function. Such knowledge can seldom be secured experimentally, and almost certainly not in a single experiment. The discussion that follows therefore assumes a more modest objective, the determination of a local maximum.

Although the location of a maximum is of primary importance, mapping the function in the neighborhood of a maximum is important for several reasons:

(1) Typically, maximization of the particular dependent variable measured in a given experiment is only one of several desiderata in choosing an alloy, so it is important to know how much would be sacrificed if the independent variables were altered to satisfy other requirements. For example, the combination of independent variables that gives the highest time to rupture may give insufficient ductility. It might then be desirable to know how much strength would be sacrificed by various changes designed to increase ductility.

(2) Knowledge of the relative importance of different independent variables is valuable in designing other experiments to find other maxima.

(3) Knowledge of the function in the region of a maximum may contribute to an understanding of the mechanism at work and may thus advance theoretical knowledge.

(4) It may not be possible to control the independent variables as closely in production as in laboratory experiments. Knowledge of the function in the neighborhood of a maximum will make it possible to judge the seriousness of departures from control.

3. DEFICIENCIES OF FACTORIAL DESIGN

The factorial design is ideally suited for experiments whose purpose is to map a function in a preassigned range of values of the independent variables.* The fact that the region is preassigned means that it is

* The term "factorial design" is used in this chapter to refer to an experimental design in which a limited number of levels of each independent variable are selected in advance and at least one test is made for each combination of the selected levels of the independent variables. See FISHER, *Design of Experiments*, Chap. VI, The Factorial Design in Experimentation.

The factorial design is in a sense the extreme example of a class of designs having in common the selection in advance of the values of the independent variables at which

feasible to lay out the design completely and specifically in advance of the experiment; the fact that the behavior of the function is desired for all possible combinations of the independent variables means that the experiment must represent all combinations in some way, which a factorial design does.

For the purposes described in the preceding section, however, the factorial design has certain deficiencies:

(1) It devotes observations to exploring regions that may turn out, in the light of the results, to be of no interest because they are far from a maximum.

(2) Because it seeks to explore a given region comprehensively, it must either explore only a small region, or explore a large region very superficially. If a small region is explored, it may turn out to contain no local maximum. The experiment would then at best indicate the direction in which to move in conducting a new experiment. If a large region is explored, it may be explored so superficially that a maximum may be missed entirely, or, if found, will be known so imperfectly that an additional experiment is required.

(3) The factorial design has the disadvantage, somewhat less fundamental than the preceding, that it neglects the fact that some of the variables are continuous and some, though discrete, are ordered. This deficiency could, however, be remedied while retaining the basic principles of the factorial design.

4. A SEQUENTIAL DESIGN

These deficiencies of the factorial design suggest that an efficient design for the present purpose ought to be sequential; that is, ought to adjust the experimental program at each stage in the light of the results of prior stages. This section outlines a particular sequential design, primarily to illustrate the direction that seems desirable in the design of metallurgical experiments of the type here considered.

Step 1. Select some particular combination of independent variables as a starting point. The combination selected should be the best advance estimate of the optimum combination.

observations are to be made. Other designs in this class may, in any particular instance, be more economical than a complete factorial and preferable to it. Economy can be gained without loss, however, only if additional knowledge is available in advance (for example, knowledge that certain interactions are negligible).

Many of the remarks in this chapter are applicable to these other designs as well as to the complete factorial. However, the chapter considers explicitly only the complete factorial design in order to have a sharp and definite contrast and to avoid complications and qualifications that have little bearing on the main issue raised in this chapter.

Step 2. Arrange the independent variables in some order.

Step 3. Make tests at the original starting point and at a series of points differing only in the value assigned the first independent variable, the other variables being held constant.* From this series of experiments, estimate the value of the first independent variable that maximizes time to rupture.† If the independent variable is continuous, it will probably be best to find the maximum by some such device as fitting a polynomial to the observations.

Step 4. Holding the first independent variable fixed at the maximizing value found in step 3 and the other independent variables, except the second, at the values originally assigned to them, repeat step 3 with the second independent variable. Repeat this process with the third, fourth, . . . , independent variable.

Step 5. After all variables have been varied (call this a "round" of experiments), the whole process can be repeated, except that the original starting point is replaced by the combination of values of the independent variables reached at the end of the first round.

Successive rounds will clearly converge to the neighborhood of a local maximum, with perhaps a few "pathological" exceptions; for, aside from statistical fluctuations, each round and each step within a round necessarily represent an improvement. The rate at which the improvements decline from round to round is likely to give some idea of how much further progress is possible and some indication of the value of additional rounds. The process of convergence may perhaps be speeded up after one or more complete rounds. For example, after the second complete

* For the present purpose the precise meaning to be attached to "the other variables being held constant" is irrelevant. For variables representing chemical composition, it can be interpreted as meaning that the relative proportions of the other variables are held constant. Alternatively, for all but one variable, it can be interpreted as meaning that the percentage a particular element forms of the total is held constant. Any combination of these two will also do, provided the method of holding other variables constant is followed consistently.

† If the independent variable is ordered, this process also could be sequentialized, with obvious advantages. For example, tests could be made (a) at the original starting point and (b) at a single other value of the first independent variable. If the tests at (b) gave a (significantly) higher time to rupture than the tests at (a), other tests would be made by moving still farther in the same direction from the original starting point. If the tests at (b) gave a shorter time to rupture, the next tests would be made by moving in the opposite direction from the starting point. This process would be continued until a value was found higher than its neighbors in both directions. This aspect of a sequential procedure is not considered in detail here because it is not germane to our main point and because practical considerations having to do with full use of experimental equipment may make it undesirable to sequentialize the experiment fully. Even though this phase of the experiment is not sequentialized, there is a real problem about designing it efficiently. See HOTELLING, "Experimental Determination of the Maximum of a Function."

round it might be desirable to move along the vector defined by the end points of the first two rounds, instead of varying the variables according to the original pattern. After one such step, the original pattern could be used again.

It will clearly be desirable in the early rounds to use rather broad intervals in varying each independent variable and to locate the maximum only very approximately. Finer and finer intervals should be used in later rounds as the maximum is approached. A consequence of this is that the process will provide only a very rough mapping of the function in regions far removed from a maximum, but a relatively fine mapping in regions near a maximum. The mapping of the region in the neighborhood of a maximum can, if desired, be filled in by a supplementary experiment, perhaps of factorial design, after the neighborhood of the maximum has been delimited with sufficient accuracy.

It may be worth repeating that nothing more is claimed for this outline of a sequential design than that it is suggestive. Numerous problems would arise in applying it to an actual experiment, and there are many possibilities of increasing its efficiency. The suggested sequential design is in large part simply an abstract and systematic statement of a rather natural, obvious, and common method of locating a maximum or minimum of a function of many variables.

5. COMPARISON OF FACTORIAL AND SEQUENTIAL DESIGNS

5.1. Number of Observations

The great advantage of a sequential design over a factorial design is that it will concentrate observations in the neighborhood of a maximum. This advantage is likely to be greater, the larger the number of independent variables and the larger the number of values of each independent variable at which observations are taken. Let n be the number of variables and suppose that observations are to be taken at k values of each variable (for the sequential design, these need not be the same values in successive rounds). Then a complete factorial design without replication will require k^n observations. A single round of the sequential design without replication will require kn observations. The observations required for a factorial design will therefore permit $k^n/kn = k^{n-1}/n$ rounds, which increases with n and with k . The number of rounds required under the sequential design will decrease as k increases, since the maximum at each step would be determined more accurately. We do not know how the number of rounds required under the sequential design varies with n —nor indeed is it easy to see how to state this question precisely. We expect, however, that the number of rounds required will not depend very sharply on n but will depend primarily on (a) the close-

ness of the original starting point to the optimum combination and (b) the size of the experimental error relative to the differences it is considered important to detect.

Consider a simple $5 \times 3 \times 3 \times 3$ factorial design, that is, one involving four independent variables, with five values of the first and three values of each of the others. Such a design requires 135 observations, without providing for replications. A single round of the sequential design, covering the same number of values of each independent variable, would require 14 observations. It would therefore be possible to make almost 10 complete rounds with the number of observations required for the factorial experiment. Fewer than 10 rounds should suffice if the original starting point is reasonably close to the maximum. More rounds might be required if the original starting point were far from a maximum; but if so little information about the location of a maximum were available, a factorial experiment might well prove fruitless.

As another example, consider an experiment to determine the optimum composition of the high-carbon vitallium-type alloys with respect to elements that have been included in various tests of this type of alloys. At least ten elements have been included in one or another trial composition. This gives nine independent variables, since the sum of the percentages must add up to 100. Suppose we are willing to use only three levels of each element. A complete factorial design without replications would then require 3^9 , or 19,683, observations. A single round of the sequential design without replications would require only 27 observations, so that it would be possible to make 729 rounds with the number of observations required for a complete factorial design. Five rounds, with duplicate observations at each level on each round, would require only 270 observations, or less than 1.5 per cent of the number required for a complete factorial design without replications. As this example indicates, the advantage of the sequential design in terms of number of observations is likely to become extremely great as the number of variables increases. And, it should be noted, the metallurgical problem in question does in fact involve many variables. The example cited is certainly conservative, since, in addition to the ten chemical elements, the strength of the alloy is likely to be affected by the solution and aging treatments, the methods of casting or of forging, and so forth.

It should be recognized that the additional observations obtained in the factorial experiment are not useless. They provide information about the behavior of the function in regions removed from a maximum, about the relative importance of the variables, and about their interactions. This information is likely to be valuable in choosing new regions within which to search for maxima and in deciding on the vari-

ables on which to concentrate in preliminary experimentation. More important still, the observations some distance from a maximum may, under some circumstances, tell something about the behavior of time to rupture in the neighborhood of that maximum; perhaps the most common circumstances when this occurs are when (a) interactions are small, or (b) there is available a fairly good approximation to the mathematical form of the function, involving relatively few parameters.

With respect to proviso (a), work on metallurgical problems suggests that interactions rarely are small. Furthermore, while the efficiency of a factorial design for finding a maximum is greater if there are no interactions than if there are interactions, so is that of a sequential design. If there are no interactions, a single round of the sequential experiment will, except for statistical fluctuations, lead directly to the maximum. Statistical fluctuations mean that successive rounds will not lead to exactly the same point; but they will tend to give much the same time to rupture, and it should become clear fairly quickly that one is in the immediate neighborhood of a maximum. Moreover, in the absence of interactions, data from successive rounds can be combined to give a better estimate of the maximum.

Proviso (b), that there be available a good approximation, involving relatively few parameters, to the mathematical form of the function, is rarely satisfied. But if it is, neither the standard factorial design nor the sequential design suggested in Sec. 4 is appropriate. The problem then is to determine as accurately as possible the values of the independent variables that maximize this function. These maximizing values depend upon the parameters of the function; the optimum design for this purpose thus depends on the form of the function and on the approximate values of its parameters. Probably the best plan is to conduct a small preliminary experiment to get a general idea of the values of the parameters and to use this information in designing a larger experiment.*

5.2. Time Trends

One real advantage of the factorial design is that it is possible, through proper randomization, to prevent the introduction of bias from any time trends that may be present. Time trends will, indeed, reduce the power of the factorial experiment to detect the effects that it is designed to measure, but they will not bias the conclusions. The sequential plan, on the other hand, is very much at the mercy of time trends; and great care would have to be taken to see that none crept in. Measures that might be adopted would include (a) running control specimens of constant composition along with the test specimens; (b) keeping a running record

* See HOTELLING, "Experimental Determination of the Maximum of a Function."

of differences between duplicate specimens to detect changes in experimental error.

6. REFERENCES

FISHER, R. A.: *The Design of Experiments*, 3d ed., Oliver and Boyd, Ltd., Edinburgh and London, 1942.

HOTELLING, HAROLD: "The Experimental Determination of the Maximum of a Function," *Annals of Mathematical Statistics*, Vol. 12 (1941), pp. 20-45.

Part III

TECHNIQUES AND TABLES

	Page
Chapter 14. Probability That Sample Means Are in Opposite Order to Population Means	375
Chapter 15. Significance of the Largest of a Set of Sample Estimates of Variance	383
Chapter 16. Inverse Sine Transformation of Proportions	395
Chapter 17. Elements of Sequential Analysis	417

CHAPTER 14

PROBABILITY THAT SAMPLE MEANS ARE IN OPPOSITE ORDER TO POPULATION MEANS

	PAGE
1. Introduction.	377
2. Probability Function	378
3. Sample Sizes	380
4. Conditions under Which the Sign of $\bar{x}_1 - \bar{x}_2$ Provides the Best Decision Function	381
5. References.	382

FIGURE

14.1 Probability That Means of Samples from Two Normal Populations Will Be in Opposite Order to Population Means.	379
--	-----

TABLE

14.1 Probability $P(\delta, N)$ that Sample Means Will Be in Opposite Order to Popula- tion Means for Selected Values of δ and N	378
--	-----

This chapter was prepared by
Churchill Eisenhart, National Bureau of Standards

CHAPTER 14

PROBABILITY THAT SAMPLE MEANS ARE IN OPPOSITE ORDER TO POPULATION MEANS

1. INTRODUCTION

When N objects are drawn independently at random from each of two populations in which some measurable characteristic x of the objects is distributed about mean values m_1 and m_2 , what is the probability that the larger of the two sample means \bar{x}_1 and \bar{x}_2 will correspond with the population having the smaller mean? In other words, if a decision about the sign of $m_1 - m_2$ is based on the sign of $\bar{x}_1 - \bar{x}_2$, what is the probability that the decision will be wrong?

Such a question arises if two alternative sources S_1 and S_2 (for example, processes for making, procedures for treating, genetic strains) yield objects of a certain kind, and the worth of each object is determined by the value of some measurable characteristic x that varies about an average m_1 for objects from S_1 and about an average m_2 for objects from S_2 . If m_1 and m_2 were known, a decision to adopt S_1 or S_2 would be determined (completely) by the sign of $m_1 - m_2$; that is, S_1 or S_2 would be chosen according as m_1 exceeds or does not exceed m_2 . When m_1 and m_2 are unknown, it is natural to base the decision on the sign of $\bar{x}_1 - \bar{x}_2$, where \bar{x}_1 and \bar{x}_2 are the average values of x for N objects drawn independently at random from S_1 and S_2 , respectively. Such decisions will be wrong, that is, opposite to the decision that would be made if m_1 and m_2 were known, whenever the sign of $\bar{x}_1 - \bar{x}_2$ is opposite to that of $m_1 - m_2$. Consequently, it is of interest to know the probability of such an occurrence and how this probability depends on the sample size N and on the absolute magnitude of the true difference, $|m_1 - m_2|$.

In Sec. 2 the probability of $\bar{x}_1 - \bar{x}_2$ having its sign opposite to that of $m_1 - m_2$ is evaluated, and its dependence on N and $|m_1 - m_2|$ studied, for the case where x is normally distributed about m_1 with a standard deviation of σ_1 for objects from S_1 , or about m_2 with standard deviation σ_2 for objects from S_2 . In Sec. 3 attention is given to the question of how large N should be in order that the risk of a wrong decision be less than β whenever $|m_2 - m_1|$ exceeds D , say. The results given in Secs. 2 and 3 are applicable, to a good approximation, in cases where x is non-normally distributed for objects from S_1 or S_2 , provided the distributions of x have finite standard deviations, which is generally the case in prac-

tical work, and N is sufficiently large. For sample sizes of 4 or larger the approximation will generally be adequate for most practical purposes when σ_1 and σ_2 are known. When σ_1 and σ_2 are unknown and N is not less than 30, σ_1 and σ_2 may be replaced by their estimates from the samples

$$s_i = \sqrt{\frac{N \sum_{j=1}^N x_{ij}^2 - \left(\sum_{j=1}^N x_{ij} \right)^2}{N(N-1)}} \quad (i = 1, 2) \quad (1)$$

and the results of Secs. 2 and 3 will not be seriously affected. In Sec. 4, the conditions under which the sign of $\bar{x}_1 - \bar{x}_2$ provides the "best" decision function for choosing between S_1 and S_2 are stated, and the problem of choosing a best decision function in other circumstances is discussed briefly.

2. PROBABILITY FUNCTION

Let \bar{x}_1 and \bar{x}_2 denote the means of N observations drawn independently at random from each of two normal populations with means m_1 and m_2 and standard deviations σ_1 and σ_2 , respectively. Then in repeated sampling $\bar{x}_1 - \bar{x}_2$ will be normally distributed about a mean $m_1 - m_2$

TABLE 14.1
PROBABILITY $P(\delta, N)$ THAT SAMPLE MEANS WILL BE IN OPPOSITE ORDER TO
POPULATION MEANS FOR SELECTED VALUES OF δ AND N

Absolute difference between population means in σ units* (δ)	Number of observations in each sample (N)										
	2	4	6	8	10	12	16	20	50	100	200
0.00	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500
0.05	0.480	0.472	0.465	0.460	0.455	0.451	0.444	0.437	0.401	0.362	0.309
0.10	0.460	0.444	0.431	0.421	0.412	0.403	0.399	0.376	0.309	0.240	0.159
0.15	0.440	0.416	0.398	0.382	0.369	0.357	0.336	0.318	0.227	0.144	0.067
0.20	0.421	0.389	0.365	0.345	0.327	0.312	0.286	0.264	0.159	0.079	0.023
0.25	0.401	0.362	0.333	0.309	0.288	0.270	0.240	0.215	0.106	0.039	0.006
0.30	0.382	0.336	0.302	0.274	0.251	0.231	0.198	0.171	0.067	0.017	0.001
0.40	0.345	0.286	0.244	0.212	0.186	0.164	0.129	0.103	0.023	0.002	0.0000
0.50	0.309	0.240	0.193	0.159	0.132	0.110	0.079	0.057	0.006	0.0002	
0.75	0.227	0.144	0.097	0.067	0.047	0.033	0.017	0.009	0.0001	0.0000	
1.00	0.159	0.079	0.042	0.023	0.013	0.007	0.002	0.001	0.0000		
1.25	0.106	0.039	0.015	0.008	0.003	0.001	0.0002	0.0000			
1.50	0.067	0.017	0.005	0.001	0.0004	0.0001	0.0000				
1.75	0.040	0.007	0.001	0.0002	0.0000	0.0000					
2.00	0.023	0.002	0.0003	0.0000							
2.50	0.006	0.0002	0.0000								
3.00	0.001	0.0000									

* Let m_1 and σ_1 denote the mean and standard deviation of the first population, m_2 and σ_2 denote the mean and standard deviation of the second population, and let $\sigma^2 = (\sigma_1^2 + \sigma_2^2)/2$; then $\delta = |m_1 - m_2|/\sigma$.

with standard deviation $\sigma \sqrt{2/N}$ where

$$\sigma^2 = \frac{\sigma_1^2 + \sigma_2^2}{2} \quad (2)$$

Consequently, the probability that the sign of $\bar{x}_1 - \bar{x}_2$ will be opposite to that of $m_1 - m_2$ is

$$P(\delta, N) = \frac{1}{\sqrt{2\pi}} \int_a^\infty e^{-\frac{t^2}{2}} dt \quad (3)$$

where

$$\delta = \frac{|m_1 - m_2|}{\sigma} \quad (4)$$

and

$$a = \delta \sqrt{\frac{N}{2}} \quad (5)$$

$P(\delta, N)$ is tabulated to 3 decimals (occasionally 4) in Table 14.1 for $\delta = 0$ to 0.30 by steps of 0.05, 0.30 to 0.50 by steps of 0.10, 0.50 to 2.00 by steps of 0.25, 2.00 to 3.00 by steps of 0.50; and for $N = 2$ to 12 by

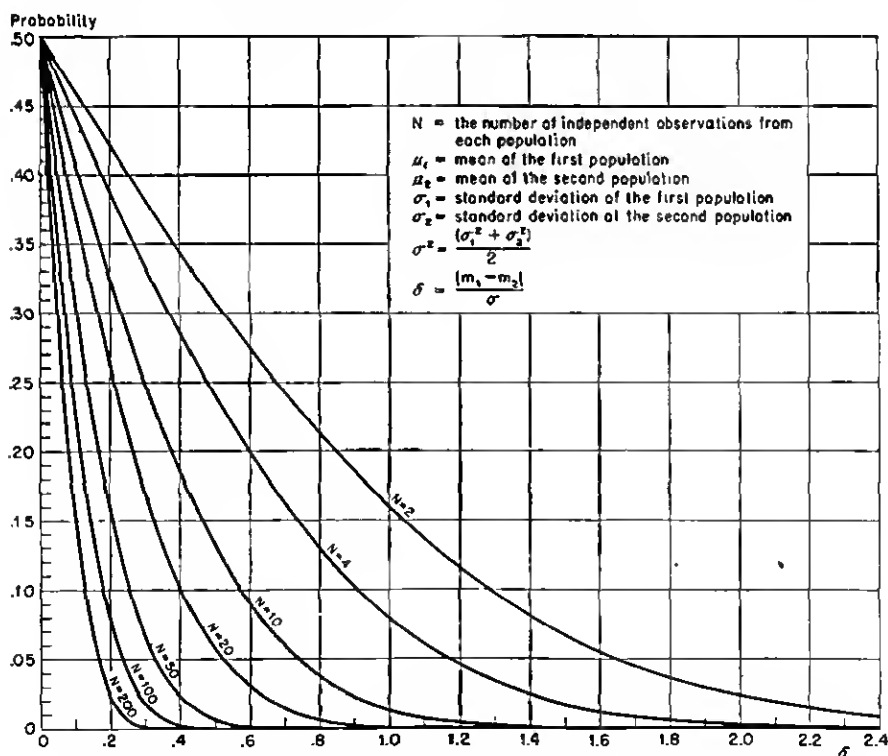


FIG. 14.1.—Probability that means of samples from two normal populations will be in opposite order to population means.

steps of 2, 16, 20, 50, 100, 200. For example, $P(0.50, 10) = 0.132$, which signifies that, with samples of 10 observations from each of two populations whose means differ by $\sigma/2$, the probability of the sample means being in opposite order to the population means is 0.132. This event may be expected to occur, therefore, more than 1 time out of 8 in the long run, under such circumstances. Clearly it is risky to base decisions on the sign of $\bar{x}_1 - \bar{x}_2$ for samples of only 10 observations each when differences of $\sigma/2$, or less, between population means are of practical importance.

In order to portray better the dependence of $P(\delta, N)$ on δ and on N , $P(\delta, N)$ has been plotted against δ in Fig. 14.1 for $N = 2, 4, 10, 20, 50, 100$, and 200. From these curves it is clear that decisions based on the sign of $\bar{x}_1 - \bar{x}_2$ will rarely be incorrect when $|m_1 - m_2|$ exceeds 2σ ($\delta = 2$), even for samples of only 4 observations each. On the other hand, if an incorrect decision is of practical importance when $|m_1 - m_2| = \sigma/2$, and if it is desired that the probability of an incorrect decision not exceed 0.01 under these circumstances, then about 50 observations from each population will be needed as a basis for decisions.

3. SAMPLE SIZES

If we choose a probability β of making an incorrect decision (a decision based on the sign of $\bar{x}_1 - \bar{x}_2$ different from that which would be made if the sign of $m_1 - m_2$ were known) and define K_β by

$$\frac{1}{\sqrt{2\pi}} \int_{K_\beta}^{\infty} e^{-\frac{t^2}{2}} dt = \epsilon \quad (6)$$

then, from (3), (4), and (5) it follows that

$$\frac{|m_1 - m_2|}{\sigma} \sqrt{\frac{N}{2}} = K_\beta \quad (7)$$

determines, for a given N and σ , the value of $|m_1 - m_2|$ for which the probability of an incorrect decision is β ; or, for a given value of $|m_1 - m_2|/\sigma$, the value of N that will be needed if the probability of an incorrect decision is to be β . Values of K_β can be obtained from Table 1.1 of Chap. 1, or values of β corresponding with various values of K from Table 1.5.

For example, if an incorrect decision is serious when $|m_1 - m_2| = \sigma/2$, and if it is desired to limit the risk of such an error to 0.01 under these circumstances, then (7) implies that at least 44 ($8 \times 2.3263^2 = 43.3$) observations will be needed from each of the populations. On the other hand, if the sampling has already been carried out, taking only 30 observations from each population, it may be some consolation to

know that the risk of an incorrect decision is only 0.05 when

$$|m_1 - m_2| = 1.6449\sigma/\sqrt{15} = 0.42\sigma$$

and is 0.01 when

$$|m_1 - m_2| = 2.3263\sigma/\sqrt{15} = 0.60\sigma.$$

4. CONDITIONS UNDER WHICH THE SIGN OF $\bar{x}_1 - \bar{x}_2$ PROVIDES THE BEST DECISION FUNCTION

In Sec. 1 it was stated that if a decision to choose S_1 or S_2 would be determined (completely) by the sign of $m_1 - m_2$ if this sign were known, it is natural to base the decision on the sign of $\bar{x}_1 - \bar{x}_2$. This raises the question of whether the sign of $\bar{x}_1 - \bar{x}_2$ is actually the best function of the data upon which to base the decision.

H. A. Simon has shown that when (a) x is normally distributed in each of the populations S_1 and S_2 , (b) the standard deviation of x is the same ($\sigma_1 = \sigma_2$) in S_1 and S_2 , (c) there is no a priori basis for a choice between S_1 and S_2 without knowledge of the values of m_1 and m_2 (or, at least, of the sign of $m_1 - m_2$), and (d) the choice between S_1 and S_2 is to be based on some symmetric function of the observed values of an equal number N of observations drawn independently at random from S_1 and S_2 , then the probability of an incorrect decision will be a minimum, whatever the values of m_1 and m_2 and of the common value of σ_1 and σ_2 , if the decision to choose S_1 or S_2 is based on the sign of $\bar{x}_1 - \bar{x}_2$. As we have seen above, the probability of an incorrect decision, when the sign of $\bar{x}_1 - \bar{x}_2$ provides the basis for decision, is determined completely by N , $\sigma = \sigma_1 = \sigma_2$, and $|m_1 - m_2|$ under these conditions.

When conditions (a), (c), and (d) above are fulfilled, but $\sigma_1 \neq \sigma_2$, then, Simon has found, there does not exist any symmetric function of the $2N$ observations having the property that when the decision to choose between S_1 and S_2 is based on the observed value of this function the probability of an incorrect decision will be a minimum whatever the values of m_1 and m_2 ; this is true even when the values of σ_1 and σ_2 are known. This is the case a fortiori when the value of either σ_1 or σ_2 is unknown. He has found, however, that if it is agreed that (d') the choice between S_1 and S_2 is to be based on some symmetric function of the differences $x_{11} - x_{21}$, $x_{12} - x_{22}$, \dots , $x_{1N} - x_{2N}$, then the sign of $\bar{x}_1 - \bar{x}_2$ is the decision function that minimizes the probability of error, whatever the values of m_1 and m_2 and of σ_1 and σ_2 .

When x is non-normally distributed in one or both of the populations, then $\bar{x}_1 - \bar{x}_2$ no longer furnishes the most efficient estimate of $m_1 - m_2$ and the sign of $\bar{x}_1 - \bar{x}_2$ will not be the best decision function upon which to base a choice between S_1 and S_2 , even when $\sigma_1 = \sigma_2$. Welch has discussed the determination of the best discriminant function upon which

to base a choice between two populations when the form of the distribution of x in each of the populations is known.

5. REFERENCES

- SIMON, HERBERT A.: "Symmetric Tests of the Hypothesis That the Mean of One Normal Population Exceeds That of Another," *Annals of Mathematical Statistics*, Vol. 14 (1943), pp. 149-154.
- WELCH, B. L.: "Note on Discriminant Functions," *Biometrika*, Vol. 31 (1939), pp. 218-220.

CHAPTER 15 SIGNIFICANCE OF THE LARGEST OF A SET OF SAMPLE ESTIMATES OF VARIANCE

	Page
1. Type of Problem.	385
2. Bartlett's Test.	387
3. Cochran's Test.	388
3.1 Tables	388
3.2 Example	388
4. Computation of Tables	389
5. References.	393

TABLES

15.1 Upper 5 Percent Levels of the Ratio of the Largest to the Sum of k Independent Estimates of Variance, Each of Which is Based on n Degrees of Freedom.	390
15.2 Upper 1 Percent Levels of the Ratio of the Largest to the Sum of k Independent Estimates of Variance, Each of Which is Based on n Degrees of Freedom.	391

This chapter was prepared by
Churchill Eisenhart, National Bureau of Standards
Herbert Solomon, Stanford University

CHAPTER 15

SIGNIFICANCE OF THE LARGEST OF A SET OF SAMPLE ESTIMATES OF VARIANCE

1. TYPE OF PROBLEM

When data relate to several different processes, to several different products, to a single process at different times, or to a particular type of product from each of several different sources, the analyst is frequently faced with the necessity of deciding whether the observed differences in variability of the data within the respective classes are consistent with the supposition that the intrinsic variability is uniform, that is, the same for each class.

If the classes are not uniform in variability, then simple comparisons of the classes in other respects may be misleading. Thus, if the within-class variability differs greatly from class to class, the mean values for the respective classes of the variable under consideration no longer provide an adequate basis for comparison, since a small mean associated with a large dispersion may imply greater frequency of occurrence of undesirable values of the characteristic than will a larger mean associated with a smaller dispersion of individual values. In such cases it may be more useful to compare the classes with respect to the probability of occurrence of an individual value greater than a specified upper limit U (as in Chap. 1) or with respect to some other feature that takes into account both the average value and the variability of the characteristic in each class. In this connection it should be recalled that the customary F test of the homogeneity of class means, which consists of comparing the observed ratio of the between-class mean square to the pooled within-class mean square, is valid only when the intrinsic within-class variability is the same for each class. Indeed, a pooled estimate of within-class variability, obtained by combining measures of the respective within-class dispersions, may be useless for practical purposes, unless there is homogeneity of within-class variability or the method of combining the within-class dispersions takes proper account of the relative importance (for example, the relative frequency of occurrence) of the respective classes under realistic conditions.

Of the various criteria that have been advanced for testing the homogeneity of a set of variance estimates, the test proposed by Bartlett is generally considered to be the best one available of the "omnibus"

variety.* An omnibus test is one that has good discriminating power with respect to a large variety of alternatives to the null hypothesis. The customary F test of the homogeneity of a set of means is often used as an omnibus test. This is the case when there are k means and the between-means mean square having $k - 1$ degrees of freedom is compared with the error mean square. But "the statistician who does not know in advance with which type of alternative to [homogeneity] he may be faced is in the position of a carpenter who is summoned to a house to undertake a job of an unknown kind and is only able to take one tool with him! Which shall it be? Even if there is an 'omnibus' tool, it is likely to be far less sensitive at any particular job than a specialized one; but the specialized tool will be quite useless under the wrong conditions."† It is therefore advisable in applications of the F test to isolate and test individually the mean squares corresponding to comparisons that have special interest a priori, or that represent comparisons between rational subgroups of the data that may have unequal (population) means for various a priori reasons. By thus adapting the F test to the circumstances of the study involved, its discriminating power is improved, at least with respect to the alternatives to homogeneity that are believed to be the most likely to exist or to be of special importance if they do exist. Bartlett has pointed out that his over-all test for homogeneity of a set of variances can be separated, in similar fashion, into parts representing comparisons of special interest between subsets of variance estimates, and the statistical significance of each part tested individually.‡ Like the F test for homogeneity of means, Bartlett's test has been shown to be unbiased and to possess various other desirable properties.§ When the issue is homogeneity of variances, Bartlett's test assumes the role played by the F test when the issue is homogeneity of means.

Bartlett's test, though applicable, is somewhat inappropriate when the alternative to homogeneity that is most likely to represent the true situation, or that is of special importance when it does obtain, is that the expected value of some one of the mean squares (variance estimates) substantially exceeds the expected values of the others, which may be homogeneous or not. By "some one" it is meant that prior to the

* BARTLETT, "Sufficiency and Statistical Tests," especially p. 273. Also see BISHOP and NAIR, "Homogeneity of a Set of Estimated Variances"; PITMAN, "Location and Scale Parameters"; and HARTLEY, "Homogeneity of a Set of Variances." Bartlett's test is described in the next section of this chapter; also in Rider, *Statistical Methods*, Chap. 7, Sec. 51, where an illustration is given. (For full citations, see Sec. 5.)

† PEARSON, "Efficiency of Statistical Tools," p. 316.

‡ BARTLETT, "Examples of Statistical Methods," especially pp. 158-159.

§ PITMAN, "Location and Scale Parameters," especially Secs. 2 to 6; also HARTLEY, "Homogeneity of a Set of Variances."

analysis of the data—or, better, prior to the collection of the data—there is no basis for identifying the anomalous one of the set. The several variance estimates may correspond, for example, to the several machines of a production line and represent the within-machine variability of products produced by the respective machines, which variability may be expected to be the same from machine to machine unless one of the machines is out of adjustment, in which event the variability of products from this machine will exceed that of products from other machines. Similarly, the several variance estimates may correspond to samples taken from a production line at various times during a shift and may be expected to be homogeneous if the process is in control but to have a high value if the process was out of control on one occasion. In situations of this type what is needed is a test of the statistical significance of the amount by which the largest of the variance estimates exceeds the others. Cochran has developed such a test and has provided a small table of 5 percent significance levels to facilitate its use.*

Cochran's test for the statistical significance of the largest of a set of variance estimates is described and its use illustrated in Sec. 3. Table 15.1, which gives 5 percent levels of the test, is an extension of Cochran's table. Table 15.2 gives 1 percent levels, which were not tabulated by Cochran. In view of the approximations used in their computation, many of the entries in these tables are not accurate to 4 decimal places, as tabulated. Their accuracy is believed to be sufficient for most practical purposes, at least until more accurate values are available. For discussion of the methods of computation see Sec. 4.

2. BARTLETT'S TEST

Let $s_1^2, s_2^2, \dots, s_k^2$ be k variance estimates distributed independently as $\chi^2\sigma^2/n$ for n_1, n_2, \dots, n_k degrees of freedom, respectively, and s^2 be the pooled variance of the k samples

$$s^2 = \frac{\sum n_i s_i^2}{n} \quad (1)$$

where

$$n = \sum n_i \quad (2)$$

Bartlett's test involves computing

$$\begin{aligned} B &= \frac{1}{C} \left(n \log_e s^2 - \sum n_i \log_e s_i^2 \right) \\ &= \frac{2.30259}{C} \left(n \log_{10} s^2 - \sum n_i \log_{10} s_i^2 \right) \end{aligned} \quad (3)$$

* COCHRAN, "Largest of a Set of Estimated Variances."

where

$$C = 1 + \frac{\sum \frac{1}{n_i} - \frac{1}{n}}{3(k-1)} \quad (4)$$

Then even for quite small values of the n_i , say, 5 or more, B has approximately the χ^2 distribution with $k - 1$ degrees of freedom. Since $C > 1$, it need not be calculated if for $C = 1$ the value of B is not significant.*

3. COCHRAN'S TEST

3.1. Tables

Let $s_1^2, s_2^2, \dots, s_k^2$ be k variance estimates distributed independently as $\chi^2\sigma^2/n$ for n degrees of freedom each, and let

$$g = \frac{\text{largest } s^2}{s_1^2 + s_2^2 + \dots + s_k^2} \quad (5)$$

be the ratio of the largest s^2 to their total. Table 15.1 gives values of g to 4 decimals that are exceeded with probability P , where $0.04875 < P \leq 0.05000$, for $n = 1$ to 10, 16, 36, 144, ∞ , and $k = 2$ to 10, 12, 15, 20, 24, 30, 40, 60, 120, ∞ . Table 15.2 gives values of g to 4 decimals that are exceeded with probability P , where $0.00995 < P \leq 0.01000$, for the same values of k and n . These two tables thus show the 5 percent and 1 percent levels of g . They are exact levels (to 4-decimal accuracy) whenever they exceed 0.5000 and in many other instances also. For example, a calculation of Cochran's implies that the entries in Table 15.1 for $n \leq 10$ and $k \leq 10$ are exact 5 percent levels to 4-place accuracy. Presumably the entries of Table 15.2 for $n \leq 10$ and $k \leq 10$ are likewise exact 1 percent levels to 4-place accuracy. Values of n and k exceeding 10 were selected for accuracy in interpolation. Thus n -wise interpolation should be carried out in terms of $12/\sqrt{n}$; k -wise interpolation, in terms of $120/k$ or $60/k$.

3.2. Example

The following are the squares of sample standard deviations obtained from 20 sets of six strength tests of cement mortar, each set being obtained from a different mixing of the same cement mortar under similar condi-

* Since this chapter went to press, Thompson and Merrington have provided "Tables for Testing the Homogeneity of a Set of Estimated Variances." Writing (3) above as $B = M/C$, they have tabled maximum and minimum values of the true 5 percent and 1 percent significance levels of M for $k = 3$ to 15 and for

$$c_1 = 3(k-1)(C-1)$$

from 0 to 5 by steps of 0.5; 5 to 10 by steps of 1; 12; and 14.

tions.* Are these 20 squared standard deviations homogeneous? In

Sample Number (S.D.) ²	1 271	2 389	3 617	4 107	5 1052	6 340	7 383	8 508	9 511	10 438
Sample Number (S.D.) ²	11 280	12 209	13 936	14 281	15 346	16 383	17 492	18 512	19 462	20 349

particular, is the standard deviation computed from the fifth sample "out of line"?

In this case $n = 5$, $k = 20$, and $g = 1,052/8,866 = 0.1187$, which is less than the corresponding 5 percent level (0.1735) given in Table 15.1. The anomalous value of the standard deviation from the fifth sample may, therefore, be attributed to chance, and the 20 sets of strength tests may be regarded as homogeneous with respect to variability of the strength determinations.

The squared standard deviations given above correspond to the definition

$$(\text{Sample standard deviation})^2 = \frac{\sum_{i=1}^6 (x_i - \bar{x})^2}{6} \quad (6)$$

where \bar{x} = sample average = $\frac{1}{6} \sum_{i=1}^6 x_i$, the x_i ($i = 1, 2, \dots, 6$) being the 6 individual strength determinations of the sample concerned, in pounds per square inch. Consequently, each value is $\frac{5}{6}$ of the corresponding variance estimate s^2 , defined by

$$s^2 = \frac{\sum_{i=1}^6 (x_i - \bar{x})^2}{5} \quad (7)$$

However, the factor $\frac{5}{6}$ is common to the numerator and denominator of g , so need not be taken into account explicitly.

4. COMPUTATION OF TABLES

Cochran has shown† that if $s_1^2, s_2^2, \dots, s_k^2$ are variance estimates distributed independently as $\chi^2\sigma^2/n$ for n degrees of freedom, and if

$$g_i = \frac{s_i^2}{s_1^2 + s_2^2 + \dots + s_k^2} \quad (i = 1, 2, \dots, k) \quad (8)$$

* DAVIES and PEARSON, "Estimating from Samples," Table IV, p. 92; a description of the tests appears on p. 77.

† Cochran's r and n correspond to our n and k , respectively.

TABLE 15.1
UPPER 5 PERCENT LEVELS OF THE RATIO OF THE LARGEST TO THE SUM OF k INDEPENDENT ESTIMATES OF VARIANCE, EACH OF WHICH IS BASED ON n DEGREES OF FREEDOM

$\frac{n}{k}$	1	2	3	4	5	6	7	8	9	10	16	36	144	∞
2	0.9985	0.9750	0.9392	0.9057	0.8772	0.8534	0.8332	0.8159	0.8010	0.7880	0.7341	0.6602	0.5813	0.5000
3	0.9669	0.8709	0.7977	0.7457	0.7071	0.6771	0.6530	0.6333	0.6167	0.6025	0.5466	0.4748	0.4031	0.3333
4	0.9065	0.7679	0.6841	0.6287	0.5895	0.5598	0.5365	0.5175	0.5017	0.4884	0.4366	0.3720	0.3093	0.2500
5	0.8412	0.6838	0.5981	0.5441	0.5065	0.4783	0.4564	0.4387	0.4241	0.4118	0.3645	0.3066	0.2513	0.2000
6	0.7808	0.6161	0.5321	0.4803	0.4447	0.4184	0.3980	0.3817	0.3682	0.3568	0.3135	0.2612	0.2119	0.1667
7	0.7271	0.5612	0.4800	0.4307	0.3974	0.3726	0.3535	0.3384	0.3259	0.3154	0.2756	0.2278	0.1833	0.1429
8	0.6798	0.5157	0.4377	0.3910	0.3595	0.3362	0.3185	0.3043	0.2926	0.2829	0.2462	0.2022	0.1616	0.1250
9	0.6385	0.4775	0.4027	0.3584	0.3286	0.3067	0.2901	0.2768	0.2659	0.2568	0.2226	0.1820	0.1446	0.1111
10	0.6020	0.4450	0.3733	0.3311	0.3029	0.2823	0.2660	0.2541	0.2439	0.2353	0.2032	0.1655	0.1308	0.1000
12	0.5410	0.3924	0.3264	0.2880	0.2624	0.2439	0.2299	0.2187	0.2098	0.2020	0.1737	0.1403	0.1100	0.0833
15	0.4709	0.3346	0.2758	0.2419	0.2195	0.2034	0.1911	0.1815	0.1736	0.1671	0.1429	0.1144	0.0889	0.0667
20	0.3894	0.2705	0.2205	0.1921	0.1735	0.1602	0.1501	0.1422	0.1357	0.1303	0.1108	0.0879	0.0675	0.0500
24	0.3434	0.2354	0.1907	0.1656	0.1493	0.1374	0.1286	0.1216	0.1160	0.1113	0.0942	0.0743	0.0567	0.0417
30	0.2929	0.1980	0.1593	0.1377	0.1237	0.1137	0.1061	0.1002	0.0958	0.0921	0.0771	0.0604	0.0457	0.0333
40	0.2370	0.1576	0.1259	0.1082	0.0968	0.0887	0.0827	0.0780	0.0745	0.0713	0.0595	0.0462	0.0347	0.0250
60	0.1737	0.1131	0.0895	0.0765	0.0682	0.0623	0.0583	0.0552	0.0520	0.0497	0.0411	0.0316	0.0234	0.0167
120	0.0998	0.0632	0.0495	0.0419	0.0371	0.0337	0.0312	0.0292	0.0279	0.0266	0.0218	0.0165	0.0120	0.0083
∞	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Let $s_1^2, s_2^2, \dots, s_k^2$ be any set of k quantities each independently distributed as χ^2/n for n degrees of freedom, and let

$$g = \frac{(\text{largest } s_i^2)}{\sum_{i=1}^k s_i^2}$$

Then, for a given pair of values of k and n , the probability P that g exceeds the corresponding tabular entry satisfies the inequality $0.04875 < P \leq 0.05000$. For further details regarding accuracy of entries, see Sec. 3 of this chapter.

TABLE 15.2
UPPER 1 PERCENT LEVELS OF THE RATIO OF THE LARGEST TO THE SUM OF k INDEPENDENT ESTIMATES OF VARIANCE, EACH OF WHICH IS BASED ON n DEGREES OF FREEDOM

$n \backslash k$	1	2	3	4	5	6	7	8	9	10	16	36	144	∞
2	0.9999	0.9950	0.9794	0.9586	0.9373	0.9172	0.8988	0.8823	0.8674	0.8539	0.7949	0.7067	0.6062	0.5000
3	0.9933	0.9423	0.8831	0.8335	0.7933	0.7606	0.7335	0.7107	0.6912	0.6743	0.6059	0.5153	0.4230	0.3333
4	0.9676	0.8643	0.7814	0.7212	0.6761	0.6410	0.6129	0.5897	0.5702	0.5536	0.4884	0.4057	0.3251	0.2500
5	0.9279	0.7885	0.6957	0.6329	0.5875	0.5531	0.5259	0.5037	0.4854	0.4697	0.4094	0.3351	0.2644	0.2000
6	0.8828	0.7218	0.6258	0.5625	0.5195	0.4866	0.4608	0.4401	0.4229	0.4084	0.3529	0.2858	0.2229	0.1667
7	0.8376	0.6614	0.5685	0.5050	0.4659	0.4347	0.4105	0.3911	0.3751	0.3616	0.3105	0.2494	0.1929	0.1429
8	0.7945	0.6152	0.5209	0.4627	0.4226	0.3932	0.3704	0.3522	0.3373	0.3248	0.2779	0.2214	0.1700	0.1250
9	0.7544	0.5727	0.4810	0.4231	0.3870	0.3592	0.3378	0.3207	0.3067	0.2950	0.2514	0.1992	0.1521	0.1111
10	0.7175	0.5358	0.4469	0.3934	0.3572	0.3308	0.3106	0.2945	0.2813	0.2704	0.2267	0.1811	0.1376	0.1000
12	0.6528	0.4751	0.3919	0.3428	0.3099	0.2861	0.2680	0.2535	0.2419	0.2320	0.1961	0.1535	0.1157	0.0833
15	0.5747	0.4069	0.3317	0.2882	0.2593	0.2386	0.2228	0.2104	0.2002	0.1918	0.1612	0.1251	0.0934	0.0667
20	0.4799	0.3297	0.2654	0.2288	0.2048	0.1877	0.1748	0.1646	0.1567	0.1501	0.1248	0.0960	0.0709	0.0500
24	0.4247	0.2871	0.2295	0.1970	0.1759	0.1608	0.1495	0.1406	0.1338	0.1283	0.1060	0.0810	0.0595	0.0417
30	0.3632	0.2412	0.1913	0.1635	0.1454	0.1327	0.1232	0.1157	0.1100	0.1054	0.0867	0.0658	0.0480	0.0333
40	0.2940	0.1915	0.1508	0.1281	0.1135	0.1033	0.0957	0.0898	0.0853	0.0816	0.0668	0.0503	0.0363	0.0250
60	0.2151	0.1371	0.1069	0.0902	0.0796	0.0722	0.0668	0.0625	0.0594	0.0567	0.0461	0.0344	0.0245	0.0167
120	0.1225	0.0759	0.0585	0.0489	0.0429	0.0387	0.0357	0.0334	0.0316	0.0302	0.0242	0.0178	0.0125	0.0083
∞	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Let $s_1^2, s_2^2, \dots, s_k^2$ be any set of k quantities each independently distributed as $\chi^2 v^2/n$ for n degrees of freedom, and let

$$g = \frac{\text{(largest } s^2\text{)}}{\sum_{i=1}^k s_i^2}.$$

Then, for a given pair of values of k and n , the probability P that g exceeds the corresponding tabular entry satisfies the inequality $0.00995 < P \leq 0.01000$. For further details regarding accuracy of entries, see Sec. 3 of this chapter.

then the probability that the largest of the ratios (8) exceeds g is given by

$$P(g) = kP_1(g) - \frac{k(k-1)}{2!}P_2(g) + \frac{k(k-1)(k-2)}{3!}P_3(g) - \dots + (-1)^{k-1}P_k(g) \quad (9)$$

where $P_1(g)$ is the probability that a specified one of the ratios exceeds g , $P_2(g)$ the probability that a specified pair of the ratios both exceed g , and so on. Clearly

$$P_k(g) = 0 \quad \text{when } g > \frac{1}{k} \quad (10)$$

for it is certain that the largest ratio will be as great as $1/k$; so the number of non-zero terms in (9) is the greatest integer less than $1/g$.

Cochran has shown that

$$P_1(g) = \frac{\int_0^1 x^{\frac{n}{2}-1} (1-x)^{\frac{n(k-1)}{2}-1} dx}{B\left[\frac{n}{2}, \frac{n(k-1)}{2}\right]} \quad 0 \leq g \leq 1 \quad (11)$$

and has given $P_2(g)$ and $P_3(g)$ in multiple integral form, from which the multiple integral form of $P_j(g)$, $j = 4, 5, \dots, k$, is apparent. He has pointed out that, since $P_2(g) < [P_1(g)]^2$ for all values of n and k , the upper α levels of significance of g can be evaluated to a good first approximation using only the first term of (9). Thus, if \bar{g}_α is determined from

$$P_1(\bar{g}_\alpha) = \frac{\alpha}{k} \quad (12)$$

it follows from (9) that

$$\alpha \left(1 - \frac{\alpha}{2}\right) < \alpha - \frac{k-1}{2k} \alpha^2 < P(\bar{g}_\alpha) \leq \alpha \quad (13)$$

that is, upper 5 percent levels of g determined from (12) will in all cases correspond to $0.04875 < P \leq 0.05000$; and, in view of (10), will be exact when they exceed $1/2$. Similarly, upper 1 percent levels determined from (12) will correspond to $0.00995 < P \leq 0.01000$ and will be exact when they exceed $1/2$.

From (11) it follows that

$$\begin{aligned} \bar{g}_\alpha(n, k) &= 1 - x_{\frac{\alpha}{k}} \\ &= \frac{F_{\frac{\alpha}{k}}}{F_{\frac{\alpha}{k}} + (k-1)} \end{aligned} \quad (14)$$

where

$$x_{\frac{\alpha}{k}} = x_{\frac{\alpha}{k}} \left[\frac{n}{2}, \frac{n(k-1)}{2} \right] \quad (15)$$

is the lower α/k level of significance of the beta-function distribution, and

$$\frac{F_{\alpha}}{\bar{k}} = \frac{F_{\alpha}}{\bar{k}}[n, n(k-1)] \quad (16)$$

is the upper α/k level of significance of the F distribution. Hence $\bar{g}_{0.05}(n, k)$ can be obtained from the tables of Thompson, or from those of Thompson and Merrington, for $k = 2, 5$, and 10 ; and $\bar{g}_{0.01}(n, k)$ can be obtained similarly for $k = 2$. The values of $\bar{g}_{0.05}$ given in Table 15.1 for $k = 2, 5$, and 10 , and of $\bar{g}_{0.01}$ given in Table 15.2 for $k = 2$, were obtained in this manner.

When n is an even integer, (11) can be reduced to a polynomial in g . Thus, when $n = 2$

$$P_1(g) = (1 - g)^{k-1} \quad (17)$$

and when $n = 4$

$$P_1(g) = (1 - g)^{2k-2}[1 + 2(k-1)g] \quad (18)$$

as Cochran has pointed out. The corresponding polynomials for $n = 6, 8$, and 10 were determined. The values of $\bar{g}_{0.05}$ and $\bar{g}_{0.01}$ given in Tables 15.1 and 15.2 for $n = 2, 4, 6, 8$, and 10 were obtained with the aid of these polynomials. In all other cases the values of $\bar{g}_{0.05}$ and $\bar{g}_{0.01}$ were evaluated from $0.05/k$ and $0.01/k$ levels of F , which, in turn, were determined by means of a modification of a procedure due to Paulson.

It is believed that as estimates of $\bar{g}_{0.05}$ and $\bar{g}_{0.01}$ the entries of Tables 15.1 and 15.2 are correct to within 1, or possibly 2, units in the fourth decimal place. The accuracy of the tabular entries as estimates of the true 5 percent and 1 percent levels of g is in general unknown, although it is known that the tabular values tend to exceed the true values. It is believed, however, that in all cases the tabular 5 percent levels correspond to $0.04875 < P \leq 0.05000$ and the tabular 1 percent levels to $0.00995 < P \leq 0.01000$. With this understanding, Tables 15.1 and 15.2 should be useful in practical work until more accurate tables become available.

5. REFERENCES

- BARTLETT, M. S.: "Properties of Sufficiency and Statistical Tests," *Proceedings of the Royal Society of London*, Vol. 160A (1937), pp. 268-282.
- : "Some Examples of Statistical Methods of Research in Agriculture and Applied Biology," *Supplement to the Journal of the Royal Statistical Society*, Vol. 4 (1937), pp. 137-183.
- BISHOP, D. J., and NAIR, U. S.: "A Note on Certain Methods of Testing for the Homogeneity of a Set of Estimated Variances," *Supplement to the Journal of the Royal Statistical Society*, Vol. 6 (1939), pp. 89-99.
- COCHRAN, W. G.: "The Distribution of the Largest of a Set of Estimated Variances as a Fraction of Their Total," *Annals of Eugenics*, Vol. 11 (1941), pp. 47-52.
- DAVIES, O. L., and PEARSON, E. S.: "Methods of Estimating from Samples the Population Standard Deviation," *Supplement to the Journal of the Royal Statistical Society*, Vol. 1 (1934), pp. 76-93.

- HARTLEY, H. O.: "Testing the Homogeneity of a Set of Variances," *Biometrika*, Vol. 31 (1939-1940), pp. 249-255.
- PAULSON, EDWARD: "An Approximate Normalization of the Analysis of Variance Distribution," *Annals of Mathematical Statistics*, Vol. 13 (1942), pp. 233-235.
- PEARSON, E. S., assisted by SEKAR, C. CHANDRA: "The Efficiency of Statistical Tools and a Criterion for the Rejection of Outlying Observations," *Biometrika*, Vol. 28 (1936), pp. 308-320.
- PITMAN, E. J. G.: "Tests of Hypotheses concerning Location and Scale Parameters," *Biometrika*, Vol. 31 (1939-1940), pp. 200-215.
- RIDER, PAUL R.: *An Introduction to Modern Statistical Methods*, John Wiley & Sons, Inc., New York, 1939, 220 + ix pp.
- THOMPSON, CATHERINE M.: "Tables of Percentage Points of the Incomplete Beta Function," *Biometrika*, Vol. 32 (1941), pp. 151-181.
- and MERRINGTON, MAXINE: "Tables of Percentage Points of the Inverted Beta (F) Distribution," *Biometrika*, Vol. 33 (1943), pp. 73-88.
- and ———: "Tables for Testing the Homogeneity of a Set of Estimated Variances," *Biometrika*, Vol. 33 (1946,) pp. 296-304. L. J.

CHAPTER 16

INVERSE SINE TRANSFORMATION OF PROPORTIONS

	PAGE
1. History of the Transformation	397
2. Nature of the Transformation	399
3. Effectiveness of the Transformation	401
4. Technical Notes	408
4.1 General Transformation to Stabilize Variance	408
4.1.1 Basic Theorem	408
4.1.2 Proof of Basic Theorem	409
4.2 Applications of the General Procedure	410
4.2.1 Proportion of Items Possessing a Particular Attribute in a Sample	410
4.2.2 Mean of a Sample from a Poisson Exponential Population	411
4.2.3 Estimate of the Variance of a Normal Population Based on n Degrees of Freedom	412
4.2.4 Correlation Coefficient Computed from a Sample from a Normal Population	413
4.3 A Method of Discovering Bartlett's Adjustment	413
5. References	414
5.1 Inverse Sine Transformation	414
5.2 Mathematical Tables	416

FIGURES

16.1 Dependence of the Variances of Three Functions of a Sample Proportion p on the Population Proportion P , When the Sample Size Is 10	403
16.2 Dependence of the Variances of Three Functions of a Sample Proportion p on the Population Proportion P , When the Sample Size Is 20	404
16.3 Dependence of the Variances of Three Functions of a Sample Proportion p on the Population Proportion P , When the Sample Size Is 30	405

TABLES

16.1 Means and Variances of Various Functions of a Sample Proportion for Selected Values of the Population Proportion When the Sample Size Is 10	400
16.2 Means and Variances of Various Functions of a Sample Proportion for Selected Values of the Population Proportion When the Sample Size Is 20	401
16.3 Means and Variances of Various Functions of a Sample Proportion for Selected Values of the Population Proportion When the Sample Size Is 30	402
16.4 Values of $\varphi_B(0)$ and $\varphi_B(1)$ for Samples of 10 to 50 Items Together with Values of the Variance of φ_B when $P = 0.5$	406

This chapter was prepared by
Churchill Eisenhart, National Bureau of Standards

CHAPTER 16

INVERSE SINE TRANSFORMATION OF PROPORTIONS

1. HISTORY OF THE TRANSFORMATION

If successive samples of n items each are drawn independently at random from a very large (infinite) population in which a proportion P of the items possess some definite attribute A , then the proportions p_1, p_2, p_3, \dots of items possessing A in the successive samples will be distributed in such a manner that as the number of independent samples is increased without limit the average of the p 's will tend to P and the mean of their squared deviations from P will tend to $P(1 - P)/n$. In the language of statistics this is expressed by saying that, if a sample of n items is drawn at random from an infinite population in which a proportion P of the items possess a definite attribute A , and if the proportion of items possessing A in the sample is denoted by p , then

$$\text{Expected value of } p = E(p) = P \quad (1)$$

and

$$\text{Variance of } p = V(p) = \frac{P(1 - P)}{n} \quad (2)$$

or

$$\text{Standard deviation of } p = \sigma_p = \sqrt{\frac{P(1 - P)}{n}} \quad (3)$$

Equation (3) or equation (2), considered in conjunction with equation (1), states that observed proportions p , based on successive independent random samples of size n , may be expected to be grouped more closely about the true proportion P when n is large than when n is small; for fixed sample size, their sampling variation about P will be greatest when P equals $\frac{1}{2}$ and will decrease toward zero as either P or $1 - P$ approaches zero. This dependence of the sampling variation of an observed proportion p upon the true proportion that it estimates, P , is a source of inconvenience in certain kinds of theoretical work and in some types of statistical analysis of research data. Basically, the inconvenience is a consequence of the fact that for purposes of statistical inference (for example, estimation of parameters, tests of agreement between observation and hypothesis) the worth or "weight" of an individual observation (here, a single observed proportion p) is generally inversely proportional to its sampling variance. Accordingly, the for-

mulas of statistical theory and the calculations of statistical analysis are simpler, in general, when the observations involved are of equal weight, that is, of equal precision.

Recognizing this fact, R. A. Fisher, in a paper on theoretical genetics published in 1922,* introduced the transformation $\cos \varphi = 1 - 2p$, where φ varies from 0 to π as p varies from 0 to 1, and utilized the fact that, when φ is computed from large samples, the variance of φ is, for all practical purposes, independent of the true proportion P .

Fisher employed this transformation to simplify the mathematical equations occurring in an application of statistical theory to a problem in genetics. In 1930 he published another paper on this problem† in which he considered the bias of the transformation in large samples and showed that his failure to make allowance for this bias in his earlier paper accounted for the discrepancy between one of the results therein and a solution to the same problem obtained in a different manner by Sewall Wright. Not until 1936 were the possibilities of this transformation in connection with statistical analysis of research data discussed in print, when three writers indicated advantages to be gained from its use in statistical analyses of data expressed in the form of observed proportions (or percentages of items counted). Bartlett,‡ on a suggestion from Yates, Fisher's coworker at the Rothamsted Experimental Station, considered the use of a related transformation ($\sin^2 \theta = p$, where θ varies from 0 to $\pi/2$; see below) as a means of rendering proportions amenable to analysis-of-variance techniques, which assume equal precision of the observations involved. With the same objective, Bliss,§ after some correspondence with Fisher, recommended the use of the angular transformation $\sin^2 \theta = p$ in the statistical analysis of field-trial data expressed in percentages (that is, 100 times the proportion of items with a given attribute in a sample) and gave an extensive table of θ (in degrees) for percentages (that is, 100 p) from 0.01 to 99.99. Zubin|| pointed out the advantages of using Fisher's transformation as a means of simplifying the calculations involved in testing the statistical significance of a difference between two observed proportions, his attention having been drawn to Fisher's papers by Hotelling. Zubin, utilizing this transformation, subsequently prepared nomographs¶ by means of which the statistical significance of the difference between two observed proportions can be determined almost at a glance. These nomographs jointly are, in a sense, the ancestors of the nomograph presented in Chap. 7 above.

* FISHER, "On the Dominance Ratio," p. 326. (For full citations, see Sec. 5.1.)

† FISHER, "The Distribution of Gene Ratios."

‡ BARTLETT, "Square Root Transformation in Analysis of Variance," p. 73.

§ BLISS, "The Analysis of Field Experimental Data Expressed in Percentages."

|| ZUBIN, "Note on a Transformation Function for Proportions and Percentages."

¶ ZUBIN, "Nomographs for Determining the Significance of the Difference."

Since 1936 a great deal has been written on the transformation of proportions to angles, to facilitate or validate various forms of statistical analysis. A fairly complete bibliography is given at the end of this chapter; it includes references to tables that have been published to facilitate the angular transformations in current use.

The remainder of this chapter is devoted to a discussion of the effectiveness of Fisher's transformation in small samples, especially the dependence on P of the expected value and the variance of φ . A simple adjustment, due to Bartlett,* is discussed, and a table (Table 16.4) of adjusted values provided to facilitate its use. More elaborate adjustments, determined by the data themselves in any given case, have been discussed by Cochran,† and tables‡ are available to facilitate their use. In the last section of this chapter the general method of determining transformations to stabilize variance is outlined, the angular transformation of Fisher derived, and several other such transformations noted. A method of discovering Bartlett's adjustment is noted, which may be useful in other situations.

2. NATURE OF THE TRANSFORMATION

Let p denote the proportion of items possessing some particular attribute in a sample of n items drawn independently at random from a very large (infinite) population of items in which a proportion P of the items possess the attribute in question. Under these circumstances the mean, variance, and standard deviation of p are functions of P , given by equations (1), (2), and (3). Let φ be an angle (in radians) determined by the transformation

$$\varphi = 2 \arcsin \sqrt{p} = \arccos (1 - 2p) \quad 0 \leq p \leq 1 \quad 0 \leq \varphi \leq \pi \quad (1)$$

the inverse of which is

$$p = \sin^2 \frac{\varphi}{2} = \frac{1 - \cos \varphi}{2} \quad 0 \leq p \leq 1 \quad 0 \leq \varphi \leq \pi \quad (5)$$

Then, when the number of observations n upon which p is based is large,

$$\begin{aligned} \text{Expected value of } \varphi &= E(\varphi) \\ &= \varphi(P) \text{ approximately} \end{aligned} \quad (6)$$

where

$$\varphi(P) = 2 \arcsin \sqrt{P} \quad (7)$$

* BARTLETT, "Some Examples of Statistical Methods," p. 168.

† COCHRAN, "The Analysis of Variance When Experimental Errors Follow the Poisson or Binomial Laws," pp. 342 ff.

‡ FISHER and YATES, *Statistical Tables*.

and

$$\text{Variance of } \varphi = V(\varphi) = \frac{1}{n} \text{ approximately}^* \quad (8)$$

An elementary derivation of this transformation is given in Sec. 4. This is the form in which the transformation was introduced by Fisher in 1922; the transformation has been employed in this form by Zubin and, with certain modifications, by the Statistical Research Group.†

Other writers, following Bartlett and Bliss, have transformed p to an angle θ equal to $\varphi/2$, whence $V(\theta) = 1/4n$ approximately for θ in radians or $821/n$ approximately for θ in degrees. Thus, when θ is expressed in radians, $V(\theta)$ has, for a wide range of values of P , approximately the value of $V(p)$ when $P = 1/2$. This advantage, if such it is, is lost, however, when θ is expressed in degrees.

TABLE 16.1
MEANS AND VARIANCES OF VARIOUS FUNCTIONS OF A SAMPLE PROPORTION FOR
SELECTED VALUES OF THE POPULATION PROPORTION WHEN THE SAMPLE SIZE
Is 10

P	$\varphi(P)$	$E(p)$	$40V(p)$	$E(\varphi)$	$10V(\varphi)$	$E(\varphi_B)$	$10V(\varphi_B)$
0.0500	0.4510	0.0500	0.1900	0.2856	1.2917	0.4757	0.4481
0.1000	0.6435	0.1000	0.3600	0.5134	1.6567	0.6241	0.7489
0.1500	0.7954	0.1500	0.5100	0.7006	1.6529	0.7632	0.9363
0.2000	0.9273	0.2000	0.6400	0.8598	1.5332	0.8939	1.0436
0.3000	1.1593	0.3000	0.8400	1.1260	1.2968	1.1350	1.1224
0.5000	1.5708	0.5000	1.0000	1.5708	1.1433	1.5708	1.1258
0.7000	1.9823	0.7000	0.8400	2.0156	1.2968	2.0066	1.1224
0.8000	2.2143	0.8000	0.6400	2.2818	1.5332	2.2477	1.0436
0.8500	2.3462	0.8500	0.5100	2.4410	1.6529	2.3784	0.9363
0.9000	2.4981	0.9000	0.3600	2.6232	1.6567	2.5175	0.7489
0.9500	2.6906	0.9500	0.1900	2.8560	1.2917	2.6659	0.4481

Explanation

Let P denote the proportion of items possessing a definite characteristic in an infinite population

p denote the proportion of items possessing this characteristic in a sample of 10 items drawn independently at random from the population

Then $\varphi(p) = 2 \arcsin \sqrt{p} = \arccos(1 - 2p)$, $0 \leq p \leq 1$, $0 \leq \varphi \leq \pi$

$\varphi_B(p) = \varphi(p)$ for $0 < p < 1$, $\varphi_B(0) = \varphi(1/40)$, $\varphi_B(1) = \pi - \varphi_B(0)$

and $E(\quad)$ denotes average or expected value of the quantity within the parentheses

$V(\quad)$ denotes variance of the quantity within the parentheses.

* If φ is measured in degrees

$$V(\varphi) = \left(\frac{180}{\pi}\right)^2 \frac{1}{n} = \frac{3282.8}{n}$$

† *Sequential Analysis*, Sec. 3.6; also Chap. 7 of this volume.

3. EFFECTIVENESS OF THE TRANSFORMATION

Apparently the only published investigation of the effectiveness of the inverse sine transformation in small samples is that of Bartlett* for the case of $n = 10$. His analysis shows that when $n = 10$, the variance of φ depends very markedly on the true proportion P . A year later, he remarked† that a good correction is to replace $p = 0$ by $p = 1/4n$, and $p = 1$ by $p = 1 - 1/4n$, although he gave no supporting evidence.

Tables 16.1 to 16.3 show, for $n = 10, 20$, and 30 , respectively, the values to 4 decimal places of $E(p)$, $4nV(p)$, $\varphi(P)$, $E(\varphi)$, $nV(\varphi)$, $E(\varphi_B)$, and $nV(\varphi_B)$ corresponding to $P = 0.05$ to 0.20 by steps of $0.05, 0.30, 0.50, 0.70$, and 0.80 to 0.95 by steps of 0.05 , where φ_B denotes the angular transformation (4) modified as suggested by Bartlett, that is,

$$\begin{aligned}\varphi_B(p) &= 2 \arcsin \sqrt{p} = \arccos(1 - 2p) & 0 < p < 1 & \quad 0 < \varphi_B < \pi \\ \varphi_B(0) &= 2 \arcsin \sqrt{1/4n}, & \varphi_B(1) &= \pi - \varphi_B(0)\end{aligned} \quad (9)$$

TABLE 16.2
MEANS AND VARIANCES OF VARIOUS FUNCTIONS OF A SAMPLE PROPORTION FOR
SELECTED VALUES OF THE POPULATION PROPORTION WHEN THE SAMPLE SIZE
IS 20

P	$\varphi(P)$	$E(p)$	$80V(p)$	$E(\varphi)$	$20V(\varphi)$	$E(\varphi_B)$	$20V(\varphi_B)$
0.0500	0.4510	0.0500	0.1900	0.3541	1.6315	0.4344	0.7247
0.1000	0.6435	0.1000	0.3600	0.5866	1.5458	0.6139	1.0138
0.1500	0.7954	0.1500	0.5100	0.7602	1.3240	0.7688	1.0974
0.2000	0.9273	0.2000	0.6400	0.9035	1.1810	0.9061	1.1051
0.3000	1.1593	0.3000	0.8400	1.1469	1.0858	1.1471	1.0784
0.5000	1.5708	0.5000	1.0000	1.5708	1.0562	1.5708	1.0561
0.7000	1.9823	0.7000	0.8400	1.9947	1.0858	1.9945	1.0784
0.8000	2.2143	0.8000	0.6400	2.2381	1.1810	2.2355	1.1051
0.8500	2.3462	0.8500	0.5100	2.3814	1.3240	2.3728	1.0974
0.9000	2.4981	0.9000	0.3600	2.5550	1.5458	2.5277	1.0138
0.9500	2.6906	0.9500	0.1900	2.7875	1.6315	2.7072	0.7247

Explanation

Let P denote the proportion of items possessing a definite characteristic in an infinite population

p denote the proportion of items possessing this characteristic in a sample of 20 items drawn independently at random from the population

Then $\varphi(p) = 2 \arcsin \sqrt{p} = \arccos(1 - 2p)$, $0 \leq p \leq 1$, $0 \leq \varphi \leq \pi$

$\varphi_B(p) = \varphi(p)$ for $0 < p < 1$, $\varphi_B(0) = \varphi(1/40)$, $\varphi_B(1) = \pi - \varphi_B(0)$

and $E(\quad)$ denotes average or expected value of the quantity within the parentheses

$V(\quad)$ denotes variance of the quantity within the parentheses.

* BARTLETT, "Square Root Transformation in Analysis of Variance," pp. 74-75.

† BARTLETT, "Some Examples of Statistical Methods," p. 168.

The mean values and variances of φ and φ_B were determined by direct calculation.*

If the inverse sine transformation completely stabilized variance in small samples, then $nV(\varphi)$ would be unity in all cases, or at least would be constant for a given value of n . That this is not the case is clear from Tables 16.1 to 16.3. Evidently, $nV(\varphi_B)$ is somewhat less variable than $nV(\varphi)$ over the range of values of P considered. The nature of the dependence of $nV(\varphi)$ and $nV(\varphi_B)$ on P is depicted graphically in Figs. 16.1 to 16.3, for $n = 10, 20$, and 30 , respectively. For purposes of comparison $4nV(p)$ has been plotted also. The following conclusions may be drawn:

(1) For $n \geq 10$ and $0.05 \leq P \leq 0.95$, $nV(\varphi)$ and $nV(\varphi_B)$ are less variable than $4nV(p)$.

TABLE 16.3

MEANS AND VARIANCES OF VARIOUS FUNCTIONS OF A SAMPLE PROPORTION FOR SELECTED VALUES OF THE POPULATION PROPORTION WHEN THE SAMPLE SIZE IS 30

P	$\varphi(P)$	$E(p)$	$120V(p)$	$E(\varphi)$	$30V(\varphi)$	$E(\varphi_B)$	$30V(\varphi_B)$
0.0500	0.4510	0.0500	0.1900	0.3385	1.6443	0.4278	0.8985
0.1000	0.6435	0.1000	0.3600	0.6119	1.3359	0.6197	1.0921
0.1500	0.7954	0.1500	0.5100	0.7757	1.1560	0.7771	1.0987
0.2000	0.9273	0.2000	0.6400	0.9134	1.0885	0.9136	1.0773
0.3000	1.1593	0.3000	0.8400	1.1516	1.0484	1.1516	1.0481
0.5000	1.5708	0.5000	1.0000	1.5708	1.0358	1.5708	1.0358
0.7000	1.9823	0.7000	0.8400	1.9900	1.0484	1.9900	1.0481
0.8000	2.2143	0.8000	0.6400	2.2282	1.0385	2.2280	1.0773
0.8500	2.3462	0.8500	0.5100	2.3659	1.1560	2.3645	1.0987
0.9000	2.4982	0.9000	0.3600	2.5297	1.3359	2.5219	1.0921
0.9500	2.6806	0.9500	0.1900	2.7531	1.6443	2.7138	0.8985

Explanation

Let P denote the proportion of items possessing a definite characteristic in an infinite population

p denote the proportion of items possessing this characteristic in a sample of 30 items drawn independently at random from the population

Then $\varphi(p) = 2 \arcsin \sqrt{p} = \arccos(1 - 2p)$, $0 \leq p \leq 1$, $0 \leq \varphi \leq \pi$

$\varphi_B(p) = \varphi(p)$ for $0 < p < 1$, $\varphi_B(0) = \varphi(H_{20})$, $\varphi_B(1) = \pi - \varphi_B(0)$

and $E(\quad)$ denotes average or expected value of the quantity within the parentheses

$V(\quad)$ denotes variance of the quantity within the parentheses.

* Binomial probabilities to 7 decimals were obtained from *Tables of the Incomplete Beta Function*; arcsin values to 6 decimals were obtained by interpolation in Hayashi's *Sieben- und mehrstellige Tafeln*, the entries of this latter table being corrected in some cases in accordance with the list of corrections given in *Mathematical Tables and Other Aids to Computation*, Vol. 1, No. 6, p. 197.

(2) For $n \geq 20$ and $0.05 \leq P \leq 0.95$, $nV(\varphi_B)$ is less variable than $nV(\varphi)$.

(3) For $n \geq 10$, and $0.075 \leq P \leq 0.925$, $nV(\varphi_B)$ is less variable than $nV(\varphi)$.

Since it is quite apparent from the foregoing that the inverse sine transformation, especially with Bartlett's correction, is advantageous

Let P denote the proportion of items in an infinite population that possess a given characteristic;

p denote the proportion of items possessing the characteristic among the 10 items drawn independently at random from the population;

$$\Phi(p) = 2 \arcsin \sqrt{p} = \arccos(1-2p);$$

$$\Phi_B(p) = \Phi(p), 0 < p < 1; \Phi_B(0) = \Phi(1/40); \Phi_B(1) = \pi - \Phi_B(0);$$

then $V_1 = 4P(1-P) = 4 \times 10 \times V(p)$

$$V_2 = 10 V(\Phi)$$

$$V_3 = 10 V(\Phi_B)$$

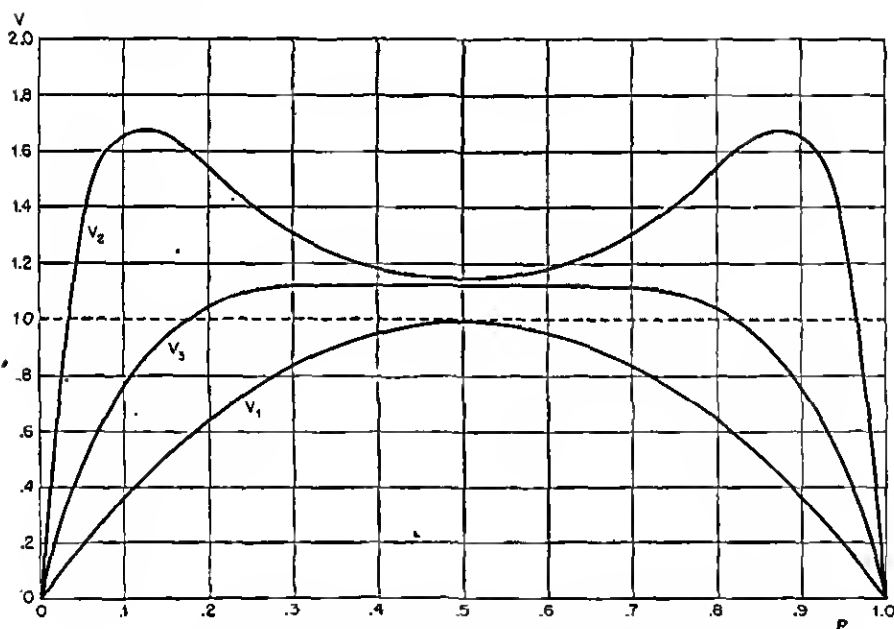


FIG. 16.1.—Dependence of the variances of three functions of a sample proportion p on the population proportion P when the sample size is 10.

from the viewpoint of variance stabilization, its effectiveness in this regard increasing rapidly as the sample size n is increased, the question arises whether estimates of P obtained by transforming back to proportions after averaging in angular units will be biased. A comparison of the values of $\varphi(P)$, $E(\varphi)$, and $E(\varphi_B)$ shown in Tables 16.1 to 16.3 reveals that $E(\varphi)$ and $E(\varphi_B)$ generally are less than $\varphi(P)$ when $P < 1/2$;

greater than $\varphi(P)$ when $P > \frac{1}{2}$; and the three are equal when $P = \frac{1}{2}$.^{*} Furthermore, for all values of n and P considered in these tables, $E(\varphi_B)$ is the closer to $\varphi(P)$. From Tables 16.1 to 16.3 it is seen that, when $0.05 \leq P \leq 0.95$, the bias $E(\varphi_B) - \varphi(P)$ is less than 15 per cent of the

Let P denote the proportion of items in an infinite population that possess a given characteristic;

p denote the proportion of items possessing the characteristic among the 20 items drawn independently at random from the population;

$$\Phi(p) = 2 \arcsin \sqrt{p} = \arccos(1-2p);$$

$$\Phi_B(p) = \Phi(p), \quad 0 < p < 1; \quad \Phi_B(0) = \Phi(1/80); \quad \Phi_B(1) = \pi - \Phi_B(0);$$

$$\text{then } V_1 = 4P(1-P) = 4 \times 20 \times V(p)$$

$$V_2 = 20 V(\Phi)$$

$$V_3 = 20 V(\Phi_B)$$

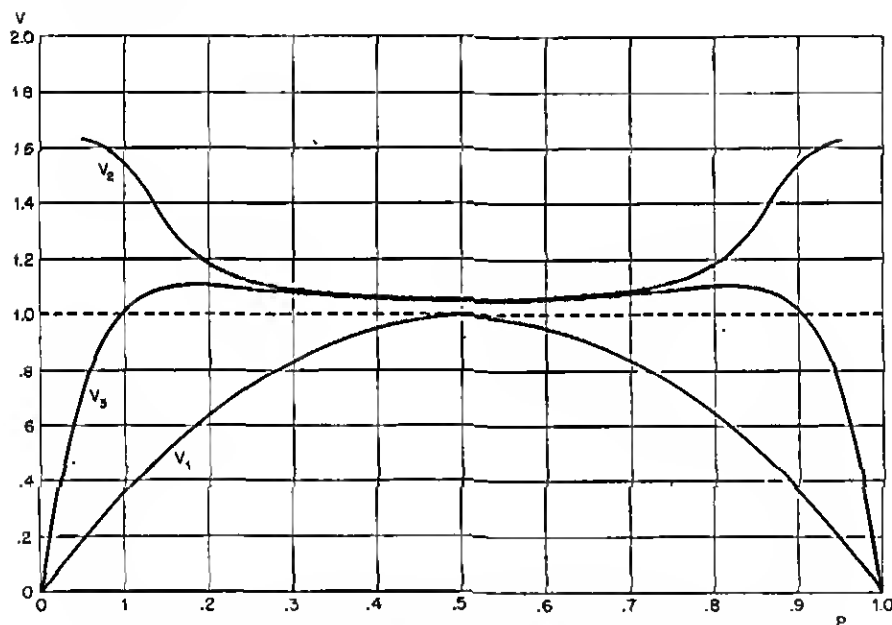


FIG. 16.2.—Dependence of the variances of three functions of a sample proportion p on the population proportion P when the sample size is 20.

standard deviation of φ_B when $n \geq 10$ and thus is of negligible magnitude for most practical purposes. Thus Bartlett's correction, in addition to its advantage from the viewpoint of stabilizing variance, tends to reduce to negligible magnitudes the biases of estimates of P obtained by reconverting averages expressed in angular units to estimated mean proportions with the aid of equation (5).

^{*} The values of $E(\varphi_B)$ for $P = 0.05$ and $P = 0.95$ when $n = 10$ are exceptions. Such exceptions can be expected to occur with φ_B in those instances in which the $p = 0$ or $p = 1$ class has a large probability of occurrence, that is, when P is close to 0 or 1 and n is small.

Values of $\varphi_B(0)$ and $\varphi_B(1)$, expressed in radians, have been tabulated in Table 16.4 for sample sizes from 10 to 50, in order to facilitate the use of Bartlett's correction. The values of $\varphi_B(0)$ and $\varphi_B(1)$ given in Table 16.4 may be used in conjunction with Zubin's "Table for Transforming Proportions to T values"* without modification; they should be divided

Let P denote the proportion of items in an infinite population that possess a given characteristic;

p denote the proportion of items possessing the characteristic among the 30 items drawn independently at random from the population;

$$\phi(p) = 2 \arcsin \sqrt{p} = \arccos(1-2p);$$

$$\phi_B(p) = \phi(p), \quad 0 < p < 1; \quad \phi_B(0) = \phi(1/20); \quad \phi_B(1) = \pi - \phi_B(0);$$

$$\text{then } V_1 = 4 P(1-P) = 4 \times 30 \times V(p)$$

$$\begin{aligned} V_2 &= 30 V(\phi) \\ &= 30 V(\phi_B) \end{aligned}$$

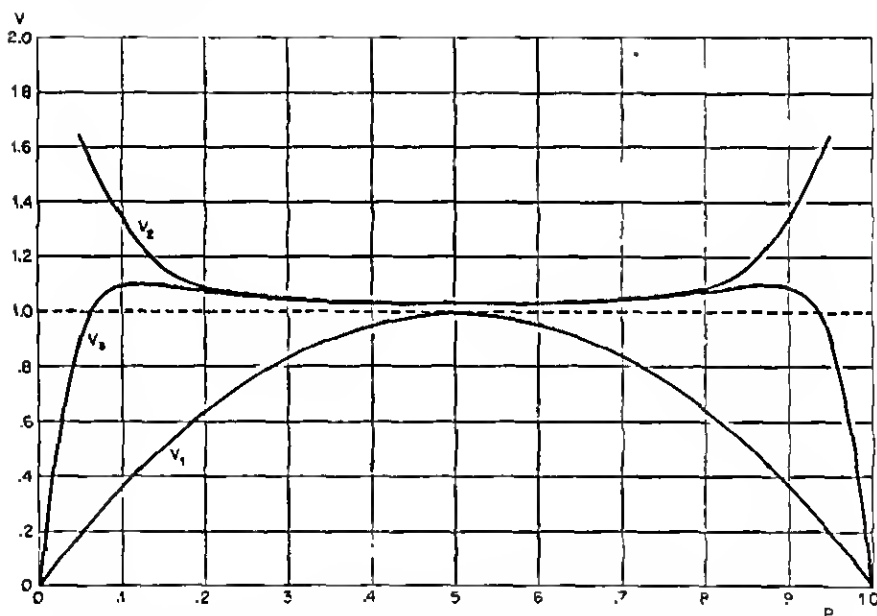


FIG. 16.3.—Dependence of the variances of three functions of a sample proportion p on the population proportion P when the sample size is 30.

by 2 before being used in conjunction with Bartlett's table†; they should be multiplied by 28.64789 before being used in conjunction with the tables of Bliss, Fisher and Yates, and Snedecor.

A previous publication of the Statistical Research Group gives a table‡ of the transformation

* ZUBIN, "Note on a Transformation," Table 4, p. 220.

† BARTLETT, "Subsampling for Attributes," Table II, p. 132.

‡ *Sequential Analysis*, Table 3.64, p. 3.57.

$$\begin{aligned}
 y(s, n) &= 2 \arcsin \sqrt{s/n} & 0 < s < n, 0 < y < \pi \\
 y(0, n) &= \sqrt{2/n} & \text{for } s = 0 \\
 y(n, n) &= \pi - \sqrt{2/n} & \text{for } s = n
 \end{aligned} \tag{10}$$

for values of n from 10 to 50. Comparison of the foregoing with equation (9) above reveals that $y(s) = \varphi_B(p)$ with $p = s/n$ for $0 < s < n$; $y(0) = \sqrt{2}\varphi_B(0)$ approximately and $y(n) = \pi - \sqrt{2}\varphi_B(0)$ approximately. Since the publication of this table of the y transformation, it has been found that Bartlett's adjustments, $\varphi_B(0)$ and $\varphi_B(1)$, are slightly more effective for stabilizing variance, especially when P is

TABLE 16.4
VALUES OF $\varphi_B(0)$ AND $\varphi_B(1)$ FOR SAMPLES OF 10 TO 50 ITEMS TOGETHER WITH VALUES OF THE VARIANCE OF φ_B WHEN $P = 0.5$

Sample size, n	$\varphi_B(0)$, radians	$\varphi_B(1)$, radians	$V_{0.5}(\varphi_B)$, radians ²	Sample size, n	$\varphi_B(0)$, radians	$\varphi_B(1)$, radians	$V_{0.5}(\varphi_B)$, radians ²
10	0.3176	2.8240	0.1126	30	0.1828	2.9588	0.0345
11	0.3027	2.8389	0.1011	31	0.1798	2.9617	0.0334
12	0.2897	2.8519	0.0918	32	0.1770	2.9646	0.0323
13	0.2782	2.8633	0.0840	33	0.1743	2.9673	0.0313
14	0.2681	2.8735	0.0775	34	0.1717	2.9699	0.0303
15	0.2589	2.8827	0.0719	35	0.1692	2.9724	0.0294
16	0.2507	2.8909	0.0670	36	0.1669	2.9747	0.0286
17	0.2431	2.8985	0.0628	37	0.1646	2.9770	0.0278
18	0.2363	2.9053	0.0591	38	0.1624	2.9792	0.0270
19	0.2299	2.9117	0.0558	39	0.1603	2.9813	0.0263
20	0.2241	2.9175	0.0528	40	0.1583	2.9833	0.0257
21	0.2187	2.9229	0.0501	41	0.1563	2.9853	0.0250
22	0.2136	2.9280	0.0477	42	0.1545	2.9871	0.0244
23	0.2088	2.9327	0.0456	43	0.1528	2.9889	0.0238
24	0.2045	2.9371	0.0436	44	0.1509	2.9907	0.0233
25	0.2003	2.9413	0.0417	45	0.1492	2.9924	0.0227
26	0.1964	2.9452	0.0401	46	0.1476	2.9940	0.0222
27	0.1927	2.9488	0.0385	47	0.1460	2.9956	0.0217
28	0.1893	2.9523	0.0371	48	0.1445	2.9971	0.0213
29	0.1860	2.9556	0.0358	49	0.1430	2.9986	0.0208
				50	0.1415	3.0001	0.0204

Explanation

Let P denote the proportion of items possessing a definite characteristic in an infinite population

p denote the proportion of items possessing this characteristic in a sample of n items drawn independently at random from the population

Then $\varphi_B(p) = 2 \arcsin \sqrt{p} = \arccos(1 - 2p)$, $0 < p < 1$, $0 < \varphi < \pi$

$\varphi_B(0) = 2 \arcsin \sqrt{1/4n}$; $\varphi_B(1) = \pi - \varphi_B(0)$

and $V_{0.5}(\varphi_B)$ denotes the variance of φ_B when $P = 0.5$.

Note: When $n > 50$, $\varphi_B(0) = \sqrt{1/4n}$, $\varphi_B(1) = \pi - \varphi_B(0)$, and $V_{0.5}(\varphi_B) = 1/n + 1/n^2$ are correct to within 1 unit in the fourth decimal place.

near 0.05 or 0.95, than the simpler adjustments $y(0, n)$ and $y(n, n)$. It is recommended, therefore, that, when special accuracy is desired, the values of $\varphi_B(0)$ and $\varphi_B(1)$ given in Table 16.4 of the present chapter be used in place of the values of $y(0, n)$ and $y(n, n)$ shown in the table of the y transformation.

From Figs. 16.1 to 16.3 it is clear that, for a fairly wide range of values of P about $P = 0.5$, the variance of φ_B , $nV(\varphi_B)$ being plotted as V_s in these figures, is quite close to its value for $P = 0.5$, say $V_{0.5}(\varphi_B)$, and that $V_{0.5}(\varphi_B)$ approaches $1/n$ as n increases. Indeed, from a consideration of these three cases ($n = 10, 20, 30$) it appears that

$$V_{0.5}(\varphi_B) = \frac{1}{n} + \frac{0.974}{n^2} + \frac{3.08}{n^3} - \frac{2.4}{n^4} \quad (11)$$

Using this formula, values of $V_{0.5}(\varphi_B)$ were computed for intermediate values of n , that is, for $10 < n < 20$ and $20 < n < 30$, and, in the absence of any other formula giving correct values for $n = 10, 20$, and 30 , this formula was used to compute values of $V_{0.5}(\varphi_B)$ for n from 31 to 50. These values are tabulated, together with the known values for $n = 10, 20$, and 30 , in Table 16.4 and provide, it is believed, a reasonably accurate picture of the convergence of $V(\varphi_B)$ toward its theoretical value of $1/n$. The values of $V_{0.5}(\varphi_B)$ given in Table 16.4 are slightly larger than the values of the variance of y given in the table of the y transformation referred to above, but for $n \geq 25$ the excess is very slight, being roughly 1 unit or less in the fourth decimal place.

Fisher and Yates have suggested that, when special accuracy is desired, observed angles be replaced by adjusted angular values in much the same manner as observed probits are replaced by adjusted probits. They have given a table to facilitate such adjustments.* The adjustments proposed by Fisher and Yates are functions of the actual proportions observed in a given instance and thus are of a wholly different type from Bartlett's adjustment, which may be regarded as a convenient rule of thumb. The theoretical basis of the adjustments advocated by Fisher and Yates has been given in a recent paper by Cochran.†

Cochran has given an excellent discussion‡ of the presentation of results of statistical analyses in which transformations of original data have been employed to facilitate their statistical analysis. Curtiss§ has provided a general mathematical theory of transformations of data to render their analysis more tractable.

* FISHER and YATES, *Statistical Tables*, Table XIV.

† COCHRAN, "The Analysis of Variance When Experimental Errors Follow the Poisson or Binomial Laws," p. 342.

‡ COCHRAN, "Analysis of Replicated Experiments," p. 168 and p. 170.

§ CURTISS, "On Transformations."

In conclusion, it must be remembered that while in large samples the variance of a transformed proportion is independent of the true proportion for most practical purposes, the variance of the transformed value φ is still proportional to $1/n$, where n is the number of observations upon which the observed proportion is based. Consequently, if p_1, p_2, p_3, \dots are proportions based on different numbers of observations n_1, n_2, n_3, \dots and if the n 's differ widely, then the variances of the corresponding angular values may be so unequal, because of the variation of the n 's, that the advantages of the transformation are lost almost entirely. Similarly, the advantages of the inverse sine transformation may be lost to a large extent when the data to be analyzed are subject to other forms of variability in addition to sampling variation so that the variance of an observed proportion p is given by $P(1-P)/n + \sigma_e^2$, where the first term represents the variation of simple sampling and the second term the extraneous variation. In a recent paper* Cochran has discussed the analysis of fractions or percentages based on different numbers of observations (a) when extraneous variation is absent and (b) when extraneous variation is present.

4. TECHNICAL NOTES

4.1. General Transformation to Stabilize Variance

4.1.1. Basic Theorem.—The transformation of random variables to stabilize variance may be based upon the following theorem:

Let θ , ($\theta_1 \leq \theta \leq \theta_2$), be a parameter of a statistical universe (population), and let T be an estimator of θ , [$T_1(\theta) \leq T \leq T_2(\theta)$], based on n observations from the universe such that

$$\left. \begin{aligned} \text{Expected value of } T &\equiv E(T) = \theta \\ \text{Variance of } T &\equiv V(T) \equiv E(T - \theta)^2 = \frac{g(\theta)}{n} \\ \text{Third moment of } T \text{ about } \theta &\equiv \mu_3(T) \equiv E(T - \theta)^3 \\ &= o\left(\frac{1}{n}\right) \text{ as } n \rightarrow \infty \dagger \\ \text{Fourth moment of } T \text{ about } \theta &\equiv \mu_4(T) \equiv E(T - \theta)^4 \\ &= o\left(\frac{1}{n}\right) \text{ as } n \rightarrow \infty \end{aligned} \right\} \quad (12)$$

* COCHRAN, "Analysis of Variance for Percentages Based on Unequal Numbers."

† By $\varphi(n) = o(n^k)$ as $n \rightarrow \infty$ we mean that $\lim_{n \rightarrow \infty} \varphi(n)/n^k = 0$. In particular, $o(1)$

means a function that tends to zero as $n \rightarrow \infty$.

By $\varphi(n) = O(n^k)$ as $n \rightarrow \infty$ we mean that $|\varphi(n)| < K \cdot n^k$ for $n \geq n_0$, where K is finite and does not depend upon n , and n_0 is some (large) value of n . In particular, $O(1)$ means a function that is bounded as $n \rightarrow \infty$.

This notation is in agreement with that introduced by E. Landau in 1909 and is now well established.

If the function

$$f(T) = \int \frac{dT}{\sqrt{g(T)}} \quad (13)$$

and its first two derivatives exist for all admissible values of T , except perhaps for a set of measure zero, and if the mean value of its second derivative and of the square of the second derivative are finite for $\theta_1 < \theta < \theta_2$ and every value of n , that is, if

$$E[f^{(2)}(T)] = O(1)$$

and

$$E[f^{(2)}(T)]^2 = O(1) \quad (14)$$

as $n \rightarrow \infty$ for $\theta_1 < \theta < \theta_2$ and $T_1(\theta) \leq T \leq T_2(\theta)$, then

$$V[f(T)] = \frac{1}{n} + o\left(\frac{1}{n}\right) \quad \text{as } n \rightarrow \infty \quad (15)$$

The first of assumptions (12) implies that T is an unbiased estimator of θ . The three further assumptions are introduced for the purposes of the theorem and are not very restrictive. Indeed, assumptions (12) are generally satisfied when T is some sort of average that has been adjusted so as to be an unbiased estimator of a population parameter of interest.

4.1.2. Proof of Basic Theorem.—Let $f(T)$ be a function of T such that its second derivative $f^{(2)}(T)$ exists for $T_1(\theta) < T < T_2(\theta)$, except perhaps for a set of points of measure zero, where $T_1(\theta) \leq T \leq T_2(\theta)$ is the admissible range of values of T , that is, $P\{T_1(\theta) \leq T \leq T_2(\theta) | \theta\} = 1$. Since $E(T) \equiv \theta$ by assumption, it follows that θ lies in the admissible range of values for T . Hence $f(T)$ may be expressed as follows, with the aid of Taylor's formula and Lagrange's form of the remainder term:

$$f(T) = f(\theta) + \frac{(T - \theta)}{1!} f^{(1)}(\theta) + \frac{(T - \theta)^2}{2!} f^{(2)}(t) \quad (16)$$

where $t = \theta + \xi_r(T - \theta)$, $0 < \xi_r < 1$, and the notation ξ_r is used to emphasize the fact that the value of ξ depends upon the value of T concerned, $T_1(\theta) \leq T \leq T_2(\theta)$.

Taking the mathematical expectation of each side of equation (16), it is found that

$$\begin{aligned} E[f(T)] &= f(\theta) + \frac{V(T)}{2!} \cdot E[f^{(2)}(t)] \\ &= f(\theta) + o(1) \quad \text{as } n \rightarrow \infty \end{aligned} \quad (17)$$

by virtue of assumption (14) and the second of assumptions (12). This shows that these assumptions, together with those regarding the existence and differentiability of $f(T)$, are sufficient to ensure that, as n increases without limit, the expected value of the function $f(T)$ converges

stochastically to $f(\theta)$, the value of the function when T assumes its expected value.

Subtracting the left and right sides of (17) from the left and right sides, respectively, of (16), squaring, and taking expected values, it is found that

$$\begin{aligned} V[f(T)] &\equiv E\{f(T) - E[f(T)]\}^2 \\ &= [f^{(1)}(\theta)]^2 \cdot V(T) + \frac{3E^2[f^{(2)}(t)]V^2(T)}{4} + \frac{E[f^{(2)}(t)]^2\mu_4(T)}{4} \\ &\quad + \frac{f^{(1)}(\theta) \cdot E[f^{(2)}(t)]\mu_3(T)}{1} \end{aligned} \quad (18)$$

In view of the assumptions (12) and (14), this becomes

$$\begin{aligned} V[f(T)] &= [f^{(1)}(\theta)]^2 \cdot V(T) + o\left(\frac{1}{n}\right) \quad \text{as } n \rightarrow \infty \\ &= [f^{(1)}(\theta)]^2 \cdot \frac{g(\theta)}{n} + o\left(\frac{1}{n}\right) \quad \text{as } n \rightarrow \infty \end{aligned} \quad (19)$$

Consequently, for the function defined by equation (13), equation (19) reduces to equation (15). This completes the proof.

Curtiss* has considered somewhat more fully the mathematical aspects of transformations of random variables to simplify their variances, and his paper should be consulted by persons interested in a comprehensive mathematical treatment.

4.2. Applications of the General Procedure

4.2.1. Proportion of Items Possessing a Particular Attribute in a Sample.—Let $\theta = P$, the proportion of items in an infinite population that possess a particular characteristic A , and let $T = p$, the proportion of items possessing A in a sample of n items drawn independently at random from the population. It is well known that

$$\begin{aligned} E(p) &= P \\ V(p) &= \frac{P(1-P)}{n} \\ \mu_3(p) &= \frac{P(1-P)(1-2P)}{n^2} \\ \mu_4(p) &= \frac{3P^2(1-P)^2}{n^2} + \frac{P(1-P)(1-6P+6P^2)}{n^3} \end{aligned} \quad (20)$$

Clearly $\mu_3(p)$ and $\mu_4(p)$ are both $o(1/n)$ as $n \rightarrow \infty$, and $g(P) = P(1-P)$. Consequently, if there is a transformation that will stabilize the variance, the theorem implies that it will be

$$f(p) = \int \frac{dp}{\sqrt{p(1-p)}} = 2 \arcsin \sqrt{p} + C = \arccos(1-2p) + C \quad (21)$$

* CURTISS, "On Transformations Used in the Analysis of Variance."

where C is an arbitrary constant, which may conveniently be taken as 0. This yields the transformation $\varphi(p)$, defined in equation (4), $\varphi(p)$ being expressed in radian measure. It is not difficult to show that the second derivative of $\varphi(p)$ satisfies the requirements of the transformation theorem for $0 < P < 1$, whence

$$V[\varphi(p)] = \frac{1}{n} + o\left(\frac{1}{n}\right) \quad \text{as } n \rightarrow \infty \quad (22)$$

4.2.2. Mean of a Sample from a Poisson Exponential Population.—Let $\theta = \mu$, the parameter (mean) of a Poisson exponential population, and let $T = \bar{x}$, the mean of a random sample of n independent observations from this population. It is well known that

$$\begin{aligned} E(\bar{x}) &= \mu \\ V(\bar{x}) &= \frac{\mu}{n} \\ \mu_3(\bar{x}) &= \frac{\mu}{n^2} \\ \mu_4(\bar{x}) &= \frac{3\mu^2}{n^2} + \frac{\mu}{n^3} \end{aligned} \quad (23)$$

Clearly $\mu_3(\bar{x})$ and $\mu_4(\bar{x})$ are both $o(1/n)$ as $n \rightarrow \infty$, and $g(\mu) = \mu$. Consequently, the theorem implies that, if there exists a transformation that will stabilize the variance, it will be

$$f(\bar{x}) = \int \frac{d\bar{x}}{\sqrt{\bar{x}}} = 2\sqrt{\bar{x}} + C \quad (24)$$

It is convenient to take $C = 0$. Bartlett* chose to drop the 2 also and recommended the transformation $y = \sqrt{\bar{x}}$. The first and second derivatives of y with respect to \bar{x} are

$$y' = \frac{1}{2\sqrt{\bar{x}}} \quad y'' = \frac{-1}{4(\bar{x})^{3/2}} \quad (25)$$

and

$$\begin{aligned} E(y') &= \frac{1}{2\sqrt{\mu}} \text{ approximately} \\ E(y'') &= \frac{-1}{4(\mu)^{3/2}} \text{ approximately} \\ [E(y'')]^2 &= \frac{1}{16\mu^3} \text{ approximately} \end{aligned} \quad (26)$$

* BARTLETT, "Square Root Transformation."

Hence, equation (18) above becomes for $y = \sqrt{\bar{x}}$

$$\begin{aligned} V(y) &= \frac{1}{4n} + \frac{3}{64\mu n^2} + \frac{1}{64} \left(\frac{3}{\mu n^2} + \frac{1}{\mu^2 n^3} \right) - \frac{1}{8\mu n^2} \text{ approximately} \\ &= \frac{1}{4n} - \frac{1}{32\mu n^2} + \frac{1}{64\mu^2 n^3} \end{aligned} \quad (27)$$

Therefore, as $n \rightarrow \infty$ for fixed μ

$$V(y) = \frac{1}{4n} + o\left(\frac{1}{n}\right) \quad (28)$$

and as $\mu \rightarrow \infty$ for fixed n

$$V(y) = \frac{1}{4n} + o\left(\frac{1}{\mu}\right) \quad (29)$$

Consequently, if either n or μ is large, $V(y) = 1/4n$, approximately.

4.2.3. Estimate of the Variance of a Normal Population Based on n Degrees of Freedom.—Let $\theta = \sigma^2$, the variance of a normal population, and let $T = s^2$, an estimate of σ^2 such that ns^2/σ^2 is distributed as χ^2 for n degrees of freedom. It is not difficult to show that

$$\begin{aligned} E(s^2) &= \sigma^2 \\ V(s^2) &= \frac{2\sigma^4}{n} \\ \mu_3(s^2) &= \frac{8\sigma^6}{n^2} \\ \mu_4(s^2) &= \frac{12(n+4)\sigma^8}{n^3} \end{aligned} \quad (30)$$

Clearly μ_3 and μ_4 are $o(1/n)$ as $n \rightarrow \infty$ and $g(\sigma^2) = (\sigma^2)^2$. Therefore, the theorem implies that, if a transformation that will stabilize the variance exists, it will be

$$f(s^2) = \int \frac{ds^2}{\sqrt{2s^2}} = \frac{\log_e s^2}{\sqrt{2}} + C = \sqrt{2} \log_e s + C \quad (31)$$

For convenience, we may take $C = 0$ and consider the transformation $y = \log_e s^2 = 2.30259 \log_{10} s^2$. Since

$$\begin{aligned} E(y') &= \frac{1}{\sigma^2} \text{ approximately} \\ E(y'') &= -\frac{1}{\sigma^4} \text{ approximately} \\ [E(y'')]^2 &= \frac{1}{\sigma^8} \text{ approximately} \end{aligned} \quad (32)$$

the type of reasoning employed in connection with the preceding example shows that

$$V(\log_e s^2) = \frac{2}{n} + o\left(\frac{1}{n}\right) \quad \text{as } n \rightarrow \infty \text{ for fixed } \sigma^2 \quad (33)$$

$$V(\log_e s^2) = \frac{2}{n} + o\left(\frac{1}{\sigma^2}\right) \quad \text{as } \sigma^2 \rightarrow \infty \text{ for fixed } n \quad (34)$$

Consequently, $V(\log_e s^2) = 2/n$, approximately, provided either n or σ^2 is sufficiently large.

4.2.4. Correlation Coefficient Computed from a Sample from a Normal Population.—Let $\theta = \rho$, the product moment coefficient of correlation in a bivariate normal population, and let $T = r$, a correlation coefficient computed from a sample of n observations drawn independently at random from the population. The mean, variance, and higher moments of r are exceedingly complicated functions of ρ and n , but when n is large and $|\rho| \ll 1$,

$$\begin{aligned} E(r) &= \rho \text{ approximately} \\ V(r) &= \frac{(1 - \rho^2)^2}{n} \text{ approximately} \\ \mu_3(r) &= o\left(\frac{1}{n}\right) \quad \text{as } n \rightarrow \infty \\ \mu_4(r) &= o\left(\frac{1}{n}\right) \quad \text{as } n \rightarrow \infty \end{aligned} \quad (35)$$

Consequently, the theorem suggests the use of the following transformation to stabilize the variance:

$$f(r) = \int \frac{dr}{1 - r^2} = \frac{1}{2} \int \left(\frac{1}{1 - r} + \frac{1}{1 + r} \right) dr = \frac{1}{2} \log_e \frac{1 + r}{1 - r} + C \quad (36)$$

Taking $C = 0$, this yields

$$z = \frac{1}{2} \log_e \frac{1 + r}{1 - r} = \tanh^{-1} r \quad (37)$$

the transformation of r introduced by R. A. Fisher.*

4.3. A Method of Discovering Bartlett's Adjustment

Let the values of

$$\varphi(p) = 2 \arcsin \sqrt{p} \quad (38)$$

* FISHER, "On the 'Probable Error' of a Coefficient of Correlation Deduced from a Small Sample," *Metron*, Vol. 1 (1921), pp. 1-32.

where

$$p = \frac{x}{n} \quad (x = 0, 1, 2, \dots, n) \quad (39)$$

be plotted on the arithmetic scale of arithmetic-probability paper against the cumulative probability

$$\sum_{r=0}^x \frac{n!}{r!(n-r)!} P^r (1-P)^{n-r} \quad (40)$$

plotted on the probability scale, for a particular value of n and a selected value of P . If $n \geq 10$ and $0.05 \leq P \leq 0.95$, it will be found that the plotted points for $2 \leq x \leq n-2$ lie very nearly on a straight line, that the points for $x=1$ and $x=n-1$ depart slightly from the extension of this line, but that the points for $x=0$ and $x=n$ lie far off the extension of this line. If the values $\varphi(0) = 0$ and $\varphi(1) = \pi$ are replaced by scores $\varphi(0) = a_n$ and $\varphi(1) = b_n$ such that the corresponding plotted points fall on a gently curving extrapolation of the curve through the plotted points for $2 \leq x \leq n-2$, it will be found that

$$\begin{aligned} a_n &= 2 \arcsin \sqrt{\frac{1}{4n}} \text{ approximately} \\ b_n &= \pi - a_n \text{ approximately} \end{aligned} \quad (41)$$

The foregoing suggests that a better adjustment than Bartlett's could be obtained by extending in both directions the line of best fit through the points for $2 \leq x \leq n-2$ and using this line to define the scores for $x=0, 1, n-1$, and n . This was tried and some improvement was noted, but for $n \geq 10$ and $0.05 \leq P \leq 0.95$ the improvement did not appear to be worth the trouble.

This procedure may be found useful for obtaining adjustments of the Bartlett type in connection with other transformations to stabilize variance.

5. REFERENCES*

5.1. Inverse Sine Transformation

BARTLETT, M. S.: "Square Root Transformation in Analysis of Variance," *Supplement to the Journal of the Royal Statistical Society*, Vol. 3 (1936), pp. 68-78.

* As this volume went to press, binomial-probability graph paper utilizing the inverse sine transformation was put out by the Codex Book Company, Inc., Norwood, Mass. The paper was designed by Frederick Mosteller and John W. Tukey, pursuant to a suggestion published in 1943 by R. A. Fisher and K. Mather (*Annals of Eugenics*, Vol. 12, p. 13). Messrs. Mosteller and Tukey plan to write an explanation of its design and uses, probably for the *Journal of the American Statistical Association*. In the meantime, they have prepared a brief statement that may be obtained from the Codex Book Company.

The paper may be ordered in two weights, heavy (no. 32,298) and light (no. 31,298). The sheets measure $8\frac{1}{2}$ by 11 in.

- : "Subsampling for Attributes," *Supplement to the Journal of the Royal Statistical Society*, Vol. 4 (1937), pp. 131-135. Table II, p. 132, gives $y = \sin^{-1} \sqrt{x}$ in radians to 4 decimals for $x = 0.01$ (0.01) 0.50.
- : "Some Examples of Statistical Methods of Research in Agriculture and Applied Biology," *Supplement to the Journal of the Royal Statistical Society*, Vol. 4 (1937), pp. 137-183.
- BATEN, WILLIAM DOWELL, and HENDERSON, EARL WILTON: "A Method of Handling Ratios by the Analysis of Variance," *Poultry Science*, Vol. 20 (1941), pp. 227-231.
- BLISS, C. I.: "The Analysis of Field Experimental Data Expressed in Percentages," *Plant Protection*, No. 12 (1937), pp. 67-77. [In Russian, with English subtitles and summary.] Table 1, pp. 70-72, gives $\arcsin \sqrt{P/100}$ in degrees to 2 decimals for (percentages) $P = 0.00$ (0.01) 1.00 (0.1) 99.00 (0.01) 100.00.
- : "The Transformation of Percentages for Use in the Analysis of Variance," *Ohio Journal of Science*, Vol. 38 (1938), pp. 9-12. Table I, p. 12, gives $\arcsin \sqrt{P/100}$ in degrees to 1 decimal place for (percentages) $P = 0.0$ (0.1) 1.0.
- CLARK, ANDREW, and LEONARD, WARREN H.: "The Analysis of Variance with Special Reference to Data Expressed in Percentages," *Journal of the American Society of Agronomy*, Vol. 31 (1939), pp. 55-66.
- COCHRAN, W. G.: "Some Difficulties in the Statistical Analysis of Replicated Experiments," *Empire Journal of Experimental Agriculture*, Vol. 6 (1938), pp. 157-175.
- : "The Analysis of Variance When Experimental Errors Follow the Poisson or Binomial Laws," *Annals of Mathematical Statistics*, Vol. 11 (1940), pp. 335-347.
- : "Analysis of Variance for Percentages Based on Unequal Numbers," *Journal of the American Statistical Association*, Vol. 38 (1943), pp. 287-301.
- CURTISS, J. H.: "On Transformations Used in the Analysis of Variance," *Annals of Mathematical Statistics*, Vol. 14 (1943), pp. 107-122.
- FISHER, R. A.: "On the Dominance Ratio," *Proceedings of the Royal Society of Edinburgh*, Vol. 42 (1921-1922), pp. 321-341.
- : "The Distribution of Gene Ratios for Rare Mutations," *Proceedings of the Royal Society of Edinburgh*, Vol. 50 (1929-1930), pp. 205-220.
- , and YATES, FRANK: *Statistical Tables for Biological, Agricultural and Medical Research*, 2nd ed., Oliver and Boyd, Ltd., London and Edinburgh, 1943, 98 + viii pp. Table XII gives $\arcsin \sqrt{P/100}$ in degrees to 1 decimal place for (percentages) $P = 0$ (1) 99. Table XIII gives $\arcsin \sqrt{p}$ in degrees to 1 decimal place for (fractions) $p = x/n$ corresponding to $n = 2$ (1) 30 and integral values of x from 1 to the largest integer less than $n/2$. Table XIV gives "angular values for adjustments of special accuracy," namely, $\varphi + \frac{1}{2} \cot \varphi$ and $\operatorname{cosec} 2\varphi$, to 1 decimal place for $\varphi = 45$ (1) 89 degrees.
- FULCHER, JOHN S., and ZUBIN, JOSEPH: "The Item Analyzer: A Mechanical Device for Treating the Four Fold Table in Large Samples," *Journal of Applied Psychology*, Vol. 26 (1942), pp. 511-522.
- SNEDECOR, GEORGE W.: *Statistical Methods Applied to Experiments in Agriculture and Biology*, 4th ed., The Iowa State College Press, Ames, 1946. Table 16.8 is a reproduction of the table published by C. I. Bliss in *Plant Protection*.
- Statistical Research Group, Columbia University, *Sequential Analysis of Statistical Data; Applications*, rev. ed., Columbia University Press, New York, 1945. Table 3.64, opposite p. 3.56 of Sec. 3, gives $y(s, n) = 2 \arcsin \sqrt{s/n}$ in radians to 4 decimals for $n = 10$ (1) 50 and $s = 1$ (1) $n - 1$, together with values of $y(0, n) = \sqrt{2/n}$ and $y(n, n) = 3.1416 - \sqrt{2/n}$ to 4 decimals and values of $V = 1/n + 1/n^2$ to 6 decimals, for $n = 10$ (1) 50.

ZUBIN, JOSEPH: "Note on a Transformation Function for Proportions and Percentages," *Journal of Applied Psychology*, Vol. 19 (1936), pp. 213-220. Table 4, p. 220, gives $T = 2 \arcsin \sqrt{p}$ in radians to 4 decimals for (proportions) $p = 0.00$ (0.01) 0.99.

———, "Note on a Graphic Method for Determining the Significance of the Difference between Group Frequencies," *Journal of Educational Psychology*, Vol. 27 (1936), pp. 431-444.

———: "Nomographs for Determining the Significance of the Differences between the Frequencies of Events in Two Contrasted Series or Groups," *Journal of the American Statistical Association*, Vol. 34 (1939), pp. 539-544.

5.2. Mathematical Tables

HAYASHI, KEIICHI: *Sieben-und mehrstellige Tafeln der Kreis-und Hyperbelfunktionen*, Julius Springer, Berlin, 1926, 283 + vi pp.

PEARSON, KARL: *Tables of the Incomplete Beta Function*, University Press, Cambridge, England, 1934, 494 + lix pp.

SALZER, H. E., and ISAACSON, E.: "Mathematical Tables—Errata, No. 35," *Mathematical Tables and Other Aids to Computation*, Vol. 1 (1943-1945), pp. 196-197. A list of errors in Hayashi's table of $\arcsin x$.

CHAPTER 17

ELEMENTS OF SEQUENTIAL ANALYSIS

	PAGE
1. Introduction	419
1.1 Nature of Sequential Tests	419
1.2 Advantages and Disadvantages	419
1.3 General Procedure	420
1.4 Simplifications	421
2. Binomial Distribution	421
2.1 Algebraic Simplification of General Procedure	421
2.2 Graphical Procedure	422
3. Normal Distribution	423
3.1 Algebraic Simplification of General Procedure	423
3.2 Graphical Procedure	423
4. Double Dichotomies	424
4.1 Null and Alternative Hypotheses	424
4.2 Algebraic Simplification of General Procedure	424
4.3 Graphical Procedure	425
5. Other Applications	426
5.1 Simple Problems	426
5.2 Complex Problems	426
6. Operating Characteristics	426
6.1 General	426
6.2 Five-point OC Curves	427
7. Average Number of Observations	427
7.1 General	427
7.2 Five-point ASN Curves	428
8. References	428

This chapter was prepared by
W. Allen Wallis, University of Chicago

CHAPTER 17

ELEMENTS OF SEQUENTIAL ANALYSIS*

1. INTRODUCTION

1.1. Nature of Sequential Tests

A sequential test of a statistical hypothesis consists of making a certain calculation after each observation (or group of observations) and deciding on the basis of this calculation whether (1) to accept the hypothesis under test, (2) to accept the alternative to that hypothesis, or (3) to suspend judgment pending the examination of more data. The criteria for these decisions are such that the hypothesis is accepted or rejected as soon as, but not before, the data are sufficient for doing so with predetermined degrees of reliability.

1.2. Advantages and Disadvantages

Sequential is superior to nonsequential analysis whenever (1) the data become available serially and (2) the cost of the data (in terms of time, labor, material, and so forth) is more or less proportional to the amount of data. Nonsequential analysis is superior whenever (1) the amount of data is fixed or (2) the cost of the data is largely overhead, hence more or less independent of the amount of data. *Superiority* consists in minimizing a set of quantities (N, α, β) , where N is the number of observations, α is the risk (that is, the probability) of erroneously rejecting the hypothesis under test, and β is the risk of erroneously accepting this hypothesis. Sequential and nonsequential tests differ in the constraints under which this set is minimized. Nonsequential tests treat N as fixed and are so designed that with either risk α or β fixed the other is minimized. Sequential tests treat the number of observations N

* Sequential analysis was developed in the Statistical Research Group in 1943, the theory principally by A. Wald and the techniques of application by numerous members of the group, including Kenneth J. Arnold, H. A. Freeman, Milton Friedman, M. A. Girshick, Edward Paulsen, A. Wald, and W. Allen Wallis.

This chapter is an extension of a memorandum by the author of the chapter, "Sequential Tests of Statistical Significance," which is cited as "SRG 180" in Appendix B of *Sequential Analysis*. A more extensive exposition of the theory than is given here will be found in Appendix B of *Sequential Analysis*, and a more extensive summary of methods of application than is given here will be found in "Sequential Tests." For a complete and rigorous account of the theory, see "Sequential Tests"; for a full account of methods of application and interpretation, including computational aids, see *Sequential Analysis*. (For full citations, see Sec. 8.)

as a variable and are so designed that, for fixed risks α and β , the expected (that is, average) number of trials \bar{N} required to reach a decision is minimized. If for a nonsequential test N is made large enough so that, with α fixed, β will not exceed a predetermined amount, this value of N will exceed (frequently by as much as 100 percent) the \bar{N} required, with a sequential test for the same α and β . Thus, when N is readily subject to variation, sequential tests are superior; when N is not readily varied, nonsequential tests are superior.*

1.3. General Procedure

The basic quantity computed after each observation in a sequential test is known in statistical literature as the "likelihood ratio." The probability of obtaining the observations actually at hand is computed first on the assumption that the hypothesis under test (designated the "null hypothesis") is true, and second on the assumption that the alternative to this hypothesis (the "alternative hypothesis") is true. If these probabilities are designated by P_0 and P_1 , respectively, the likelihood ratio is simply P_1/P_0 . In a sequential test it is computed after each observation (or group of observations), each computation being based on all the observations available. If the likelihood ratio ever reaches a certain level A ($A > 1$), the collection of data (experiment) halts and the alternative hypothesis is accepted. If the likelihood ratio ever falls to a certain level $1/B$ ($B > 1$), the experiment ceases and the null hypothesis is accepted. When the likelihood ratio is between A and $1/B$, the evidence is insufficient for either decision with the required reliability. The required reliability, that is, the α and β of the preceding paragraph, completely determines A and B ; in fact, $A = (1 - \beta)/\alpha$ and $B = (1 - \alpha)/\beta$.

Since in most cases the successive observations are independent, the likelihood ratio for a set of observations is simply the likelihood ratio for the last observation multiplied by that for the set of preceding observations. Consequently, using the logarithm of the likelihood ratio reduces the arithmetic to addition and subtraction. After each observation, simply add $\log P_1$ to and subtract $\log P_0$ from the algebraic sum of such quantities for all preceding observations. If this sum ever reaches

$$a = \log A = \log \frac{1 - \beta}{\alpha} \quad (1)$$

accept the alternative hypothesis; if it ever falls to $-b$, where

* A detailed discussion of the conditions under which sequential analysis is advantageous and those under which it is disadvantageous is given in Statistical Research Group, *Sampling Inspection*, pp. 33-38 and 91-97. Although the discussion there is in terms of specific circumstances, its generalization is obvious.

$$b = \log B = \log \frac{1 - \alpha}{\beta} \quad (2)$$

accept the null hypothesis. Otherwise, continue the experiment.

1.4. Simplifications

The preceding paragraph is applicable whatever the null and alternative hypotheses may be, provided only that all parameters of each hypothesis are uniquely specified. In particular problems, the procedure can usually be simplified by expressing $\log P_1$ and $\log P_0$ directly in terms of the observations, then adjusting the termination levels to simplify the expression. This is illustrated below for three common tests: (1) for the probability of success in a binomial distribution; (2) for the mean in a normal distribution; and (3) for the difference in probability of success between two binomial distributions. The arithmetic can be reduced in the first and third cases to mere counting and in the second case to simple addition.

2. BINOMIAL DISTRIBUTION

2.1. Algebraic Simplification of General Procedure

Suppose it is required to determine whether the proportion p of successes, from a certain type of operation that results in either success or failure, is p_0 . The alternative against which this is to be tested is that $p = p_1$ ($p_1 > p_0$). The value of p_0 may be the minimum acceptable proportion for the operation, it may be a value observed from long experience with similar operations, or it may have been deduced from theoretical reasoning. The value of p_1 may be the least excess over p_0 worth detecting, the proportion expected on theoretical grounds, and so forth. Suppose that, after N operations, S successes have occurred. The probability of this happening (in the sequence actually observed) is $p_1^S(1 - p_1)^{N-S}$ under the alternative hypothesis and $p_0^S(1 - p_0)^{N-S}$ under the null hypothesis. The likelihood ratio is therefore

$$\left(\frac{p_1}{p_0}\right)^S \left[\frac{(1 - p_1)}{(1 - p_0)}\right]^{N-S}$$

and its logarithm is

$$S \log \left(\frac{p_1}{p_0}\right) + (N - S) \log \left[\frac{(1 - p_1)}{(1 - p_0)}\right]$$

The hypothesis that $p = p_0$ is to be rejected, and the hypothesis that

$p = p_1$ accepted, if this is ever as great as a , that is, if S ever reaches

$$S_1 = \frac{a + N \log \left(\frac{1 - p_0}{1 - p_1} \right)}{\log \left[\frac{p_1(1 - p_0)}{p_0(1 - p_1)} \right]} \quad (3)$$

This is simply a linear function of N with positive intercept. Similarly, the hypothesis that $p = p_0$ is to be accepted if S is ever as small as

$$S_0 = \frac{-b + N \log \left(\frac{1 - p_0}{1 - p_1} \right)}{\log \left[\frac{p_1(1 - p_0)}{p_0(1 - p_1)} \right]} \quad (4)$$

another (and parallel) linear function of N with negative intercept.

2.2. Graphical Procedure

Thus, the simplest procedure is to prepare a chart with N on the horizontal and S on the vertical axis. On this chart the two parallel lines S_1 and S_0 are drawn. After each observation is obtained, the total number of successes observed is plotted against the total number of observations made. If, for any N , S is as great as S_1 , discontinue the experiment and accept the hypothesis that $p = p_1$. If, for any N , S is as small as S_0 , discontinue the experiment and accept the hypothesis that $p = p_0$. When S is between S_0 and S_1 , no decision is possible with a risk as small as α or β . A variation of this procedure is to plot the number of failures $F (= N - S)$ on the horizontal axis instead of N , retaining S for the vertical scale. Then the two decision lines become, respectively,

$$S'_1 = \frac{a + F \log \left(\frac{1 - p_0}{1 - p_1} \right)}{\log \frac{p_1}{p_0}} \quad (5)$$

and

$$S'_0 = \frac{-b + F \log \left(\frac{1 - p_0}{1 - p_1} \right)}{\log \frac{p_1}{p_0}} \quad (6)$$

Caution: Be sure that the same logarithmic base is used for a and b as is used elsewhere in S_1 and S_2 .

3. NORMAL DISTRIBUTION

3.1. Algebraic Simplification of General Procedure

Suppose the standard deviation of a normal (Gaussian) distribution is known to be σ and that it is required to test the null hypothesis that the mean m is m_0 against the alternative hypothesis that $m = m_1$ ($m_1 > m_0$). If N observations, x_1, x_2, \dots, x_N , are obtained, the probability of this sequence is

$$(\sigma \sqrt{2\pi})^{-N} \exp \left\{ -\frac{1}{2\sigma^2} \left[\sum_{i=1}^N (x_i - m_0)^2 \right] \right\} \quad (7)$$

under the null hypothesis and the same expression, except with m_1 replacing m_0 , under the alternative hypothesis. From these probabilities the *natural* logarithm of the likelihood ratio is found to be

$$\frac{m_1 - m_0}{\sigma^2} \left(\sum_{i=1}^N x_i - \frac{m_0 + m_1}{2} N \right) \quad (8)$$

The hypothesis that $m = m_1$ is to be accepted if this is ever as great as a , that is, if Σx is ever as great as

$$M_1 = \frac{a\sigma^2}{m_1 - m_0} + \frac{m_1 + m_0}{2} N \quad (9)$$

Similarly, the hypothesis $m = m_0$ is to be accepted if Σx is ever as small as

$$M_0 = \frac{-b\sigma^2}{m_1 - m_0} + \frac{m_1 + m_0}{2} N \quad (10)$$

3.2. Graphical Procedure

As in the case of the binomial, prepare a chart with N on the horizontal axis and Σx on the vertical axis, and draw on it the two parallel straight lines M_1 and M_0 , of which M_1 has a positive and M_0 a negative intercept. As each observation is obtained, add it to the sum of all previous observations and plot the total against N . If the plotted point is ever as high as M_1 , terminate the experiment and accept the hypothesis that $m = m_1$. If it is ever as low as M_0 , terminate the experiment and accept the hypothesis that $m = m_0$. When it is between M_0 and M_1 , no decision can be reached without a risk of error exceeding α or β .

Caution: Be sure that a and b are *natural* logarithms. (Natural logarithms are 2.3 times the corresponding common logarithms.)

4. DOUBLE DICHOTOMIES

4.1. Null and Alternative Hypotheses

Data from two different operations, each of which results in either success or failure, constitute a double dichotomy. To determine sequentially whether the proportions of successes are the same for the two operations (which is logically identical with testing whether the two operations are represented in the same proportion among the successes as among the failures), set up the null hypothesis that the ratio of successes to failures is the same for the two operations, and the alternative hypothesis that the ratio of successes to failures is u ($u > 1$) times as great for the second operation as for the first. Thus, if p_1 and p_2 are the proportions of successes for the two operations, the null hypothesis is that $\frac{p_2/(1-p_2)}{p_1/(1-p_1)} = 1$, which is equivalent to $p_1 = p_2$. The alternative hypothesis is that $\frac{p_2/(1-p_2)}{p_1/(1-p_1)} = u$, which is equivalent to the relation $p_2 = up_1/[1 + p_1(u-1)]$. Then collect observations in pairs, each pair containing one observation for each operation. Those pairs in which both operations succeed or both fail are disregarded, since they throw no light on the question of which operation yields the higher proportion of successes. Only the residual pairs, in which one and only one operation results in a success, are considered in the remainder of this section; these residual pairs will hereafter be called successes if the operation expected under the alternative hypothesis to be superior produces a success.

4.2. Algebraic Simplification of General Procedure

Under the null hypothesis, the proportion of such successes among the residual pairs will be $\frac{1}{2}$. Under the alternative hypothesis, the proportion of such successes will be $u/(1+u)$. Thus, the problem reduces to that of the binomial distribution discussed in Sec. 2. If S is the number of successes and if F is the number of failures from N residual pairs ($S + F = N$), the logarithm of the likelihood ratio may be written

$$S \log \frac{2u}{1+u} + F \log \frac{2}{1+u} \quad (11)$$

The alternative hypothesis (that the second operation is superior) is to be accepted if this is ever as great as a ; this will occur if, for any F , S is as much as

$$S_1 = \frac{a + F \log \frac{1+u}{2}}{\log \frac{2u}{1+u}} \quad (12)$$

a linear function of F with positive intercept. Similarly, the null hypothesis (that the two operations are equally good) is to be accepted if the logarithm of the likelihood ratio is ever as small as $-b$, which will occur if, for any F , S is as small as

$$S_0 = \frac{-b + F \log \frac{1+u}{2}}{\log \frac{2u}{1+u}} \quad (13)$$

a linear function of F , parallel to S_1 but with negative intercept.

4.3. Graphical Procedure

Thus, the simplest procedure is to prepare a chart on which the horizontal axis represents F , the number of residual pairs in which a failure has occurred with the operation expected under the alternative hypothesis to be superior, and the vertical axis represents S , the number of residual pairs in which that operation has succeeded. Draw on this chart the two parallel straight lines S_0 and S_1 . After each residual pair is observed, plot a point whose coordinates represent the total number of successes and failures among all residual pairs obtained so far. If, for any value of F , S is as great as S_1 , halt the experiment and conclude that the second operation is superior. If, for any value of F , S is as little as S_0 , halt the experiment and conclude that the two operations are equally good. When S is between S_0 and S_1 , no conclusion can be reached without a risk of error in excess of α or β . An alternative procedure is to let the horizontal scale represent the number of residual pairs N ($= S + F$), in which case the decision lines become, respectively,

$$S'_1 = \frac{a + N \log \frac{1+u}{2}}{\log u} \quad (14)$$

and

$$S'_0 = \frac{-b + N \log \frac{1+u}{2}}{\log u} \quad (15)$$

Caution: Be sure that the same logarithmic base is used for a and b as is used elsewhere in S_0 and S_1 .

5. OTHER APPLICATIONS

5.1. Simple Problems

Obviously, the general procedure and the simplifications described in Secs. 1.3 and 1.4 can be applied to a wide range of problems. The application is straightforward whenever the problem is simple, in that a single parameter θ is under investigation and the purpose of the analysis is to discriminate between a null hypothesis that this parameter lies below above some level θ_0 and an alternative hypothesis that it lies above below another level θ_1 , where $\theta_1 > \theta_0$ [$\theta_1 < \theta_0$]. For example, procedures for testing the mean of a Poisson distribution and for testing the standard deviation of a normal distribution are easily derived from the general procedure. More complicated problems can sometimes be reduced to a simple form for which the procedure is straightforward, as is illustrated by the case of double dichotomies.

5.2. Complex Problems

Sequential procedures have also been worked out successfully for certain more complicated problems. Important examples are (1) testing the null hypothesis that the mean of a normal distribution has a certain value m_0 against the two-sided alternative hypothesis that the mean is either greater than m_1 or less than $2m_0 - m_1$ ($m_1 > m_0$); (2) testing the same null and alternative hypotheses as in Sec. 3, but with no information about the standard deviation other than that given by the sequential sample (the sequential equivalent of Student's test); (3) testing the standard deviation of a normal distribution, with no information about the mean other than that given by the sequential sample; (4) testing the fraction of a normal distribution exceeding a certain level, with no information about the mean or standard deviation other than that given by the sequential sample.

6. OPERATING CHARACTERISTICS

6.1. General

Sequential tests are determined by four quantities, the values θ_0 and θ_1 specified by the null and alternative hypotheses for the parameter being investigated and the values α and β of the two risks of error. For simple problems involving independent observations, for example, those described in Secs. 2, 3, and 4, the sequential-test procedure involves only three parameters, the slope s and the two intercepts $-h_1$ and h_2 of the two decision lines. Obviously, then, many combinations of θ_0 , θ_1 , α , and β lead to the same sequential test. By finding these combinations, we can determine the probability that the test will lead to acceptance of the null hypothesis for any possible value of θ , not merely θ_0 and θ_1 .

The function (curve) giving the probability of acceptance L_θ for every possible value of θ is known as the operating-characteristic function (OC curve) of the test procedure; and $1 - L_\theta$ is known as the power function.

6.2. Five-point OC Curves

Although the equations of these curves are known, it ordinarily suffices to find five easily determined points on them. Two points are known from the fact that at the extreme values of θ , for example, at $p = 0$ and $p = 1$ in the case of the binomial distribution, the probabilities of acceptance are 1 and 0. Two more points are known from the fact that the test was obtained in such a way that at θ_0 and θ_1 the probabilities of acceptance are $1 - \alpha$ and β . A fifth, and intermediate, point results from the fact that the probability of accepting the null hypothesis is

$$\frac{h_1}{h_1 + h_2}$$

(which is $\frac{1}{2}$ if $\alpha = \beta$) when θ is such that the expected value of each term in the cumulated sum is s , for example, when the parameter of a binomial distribution is $p = s$, when the mean of a normal distribution is $m = s$, or when the standard deviation of a normal distribution is $\sigma = \sqrt{s}$.

7. AVERAGE NUMBER OF OBSERVATIONS

7.1. General

The average number of observations \bar{N} necessary to reach a decision will depend upon the risks of error and upon the divergence between the null and alternative hypotheses. \bar{N} will be greater the smaller α , the smaller β , or the smaller the divergence between the null and alternative hypotheses. Furthermore, it will have one value, \bar{N}_0 , when the null hypothesis is true and another, \bar{N}_1 , when the alternative hypothesis is true; in general its value \bar{N}_θ will depend upon the true value θ of the parameter being tested. The function (curve) giving the average number of observations \bar{N}_θ for every possible value of θ is known as the average sample number function (ASN curve). Its equation may be written

$$\bar{N}_\theta = \frac{(1 - L_\theta)a - L_\theta b}{\bar{z}_\theta} \quad (16)$$

where L_θ is the probability, when the true value of the parameter is θ , that the test will result in accepting the null hypothesis, and \bar{z}_θ represents the average value of the logarithm of the likelihood ratio when the true value of the parameter is θ . In the case of the binomial distribution, for example, the likelihood ratio is either p_1/p_0 (when a success occurs),

or $(1 - p_1)/(1 - p_0)$ (when a failure occurs). If the true proportion of successes is p ,

$$\begin{aligned}\bar{z}_p &= p \log \frac{p_1}{p_0} + (1 - p) \log \left(\frac{1 - p_1}{1 - p_0} \right) \\ &= \log \frac{1 - p_1}{1 - p_0} + p \log \left[\frac{p_1(1 - p_0)}{p_0(1 - p_1)} \right]\end{aligned}\quad (17)$$

7.2. Five-point ASN Curves

Five points on the ASN curve are readily obtainable from the five known points on the OC curve. Two points are obtained from the extreme values of θ and the corresponding probabilities of acceptance, 1 and 0. Two more points, corresponding with θ_0 and θ_1 , are obtained by taking L_s equal to $1 - \alpha$ and β , respectively. The fifth, intermediate, point is obtained by multiplying together h_1 and h_2 and dividing the product by the variance of a term in the cumulated sum when θ is such that the expected value of each term is s ; for example, the divisor of $h_1 h_2$ in testing the binomial proportion is $s(1 - s)$, in testing the mean of a Poisson distribution it is s , in testing the mean of a normal distribution of known standard deviation σ it is σ^2 , in testing the standard deviation of a normal distribution it is $2s^2$. This fifth value, \bar{N}_s , is usually (but not necessarily) near the maximum of the ASN curve.

For a given value of θ , sampling fluctuations will cause \bar{N} to vary from one sequential analysis to another, using the same values of h_1 , h_2 , and s . The distribution of \bar{N} is skewed in such a way that most samples require fewer than \bar{N}_s observations; the variability is such that the sample size rarely exceeds $3\bar{N}_s$. For usual combinations of θ_0 , θ_1 , α , and β , the ASN curve falls off sharply from its peak and \bar{N}_0 and \bar{N}_1 are substantially less than \bar{N}_s ; this is not necessarily the case, however, and in fact it is possible for the maximum of the ASN curve to occur outside the interval θ_0 to θ_1 , although $\theta = s$ is always between θ_0 and θ_1 .

8. REFERENCES

- FREEMAN, H. A., and OTHERS: *Sequential Analysis of Statistical Data: Applications*. SRG Report 255, submitted by the Statistical Research Group, Columbia University, to the Applied Mathematics Panel, National Defense Research Committee, July, 1944. Now unavailable.
- Statistical Research Group, Columbia University: *Sampling Inspection*, McGraw-Hill Book Company, Inc., New York and London, 1947.
- : *Sequential Analysis of Statistical Data: Applications*, rev. ed., Columbia University Press, New York, 1945.
- : *Sequential Tests of Statistical Significance*. SRG Memorandum 180, submitted by the Statistical Research Group, Columbia University, to the Applied Mathematics Panel, National Defense Research Committee, April, 1944. Now unavailable.

- WALD, A.: *Sequential Analysis*, John Wiley & Sons, Inc., New York, 1947, 212 + xii pp.
- : *Sequential Analysis of Statistical Data: Theory*. SRG Report 75, submitted by the Statistical Research Group, Columbia University, to the Applied Mathematics Panel, National Defense Research Committee, September, 1943. Now unavailable.
- : "Sequential Tests of Statistical Hypotheses," *Annals of Mathematical Statistics*, Vol. 16 (1945), pp. 117-186. Reprints obtainable from the Institute of Mathematical Statistics, 116 Rackham Hall, Ann Arbor, Michigan.

INDEX*

A

- A: adjustment constant, 37
 - use of, to simplify graphical procedure, 36-41
- A: critical value of likelihood ratio, in sequential analysis, 420
- A: critical value of normally distributed test function, 61
 - use of, in general formula for critical level with single sample, 61-63
 - use of, in general formula for size of single sample, 61-63
- A: function appearing in formulas for sequential variables inspection, 84
- A_k: acceptance number, 237
 - (See also Acceptance number)
- a: critical value of λ in sequential analysis, 84, 420
- a: multiple of σ in formula for mean of distribution of s , 58
 - formula for, 58
 - reference to table of, 58n.
 - relation to c_2 , 58n.
- a: ratio of expected value of s to σ , in normal samples, 58
 - (See also a: multiple of σ)
- a: ratio of width of grouping interval to σ , 197
- Abandoning experiment prior to completion, 353-362
- Abernathy, John R., 194, 222
- Absolute probability, 251
- Absolute value, 162, 377, 379-381
- Accept, 13
 - meaning of, 14
- Acceptable quality, of average, 61, 423
 - of dispersion, 229, 269, 278
 - of fraction defective (see Acceptable-quality level)
 - of range in samples of k , 228
 - of standard deviation, 229, 269, 278
- Acceptable-quality level (AQL), 11, 86
 - definition of, 11, 45n., 46
 - determination of, 45, 46
 - discrepancy in, 21, 22, 25, 26
 - intended, 22
 - meaning of, 11, 45n., 46
 - for normal inspection, 45
 - in reduced inspection, 45
 - relation of, to OC curve, 16, 17
 - to tolerance limits, 46, 47
 - selection of, 45, 46
 - table of, 22-25
 - for tightened inspection, 45
 - true, 22
- Acceptance criterion, in analysis of variance, 312, 313
 - for difference of means, σ known, 61, 62
 - with sequential sampling, 423
 - for difference of proportions, 253-255, 263, 264
 - by exact procedure, 251-253
 - incorrect formula for, 256
 - with sequential sampling, 424, 425
 - for double dichotomies, approximate, 254, 255, 263, 264
 - exact, 251-253
 - incorrect, 256
 - with sequential sampling, 424, 425
 - with fixed number of "successes," 356
 - general, in sequential analysis, 420, 421
 - for single sample, 61, 62
 - for "immediate acceptance," in variables inspection for fraction defective, 34, 37, 41, 67, 69, 70
 - for mean, in sequential analysis, with σ known, 423
 - in single-sample test of, with σ known, 61-62
 - omitted, in sequential analysis, 358
 - for proportion, in sequential analysis, 421, 422
 - in single-sample test of, 260n., 263, 264
 - when range in samples of k determines lot quality, using sequential analysis, 232-234
 - using single sample, 229, 232
 - for ratio of standard deviations, in single-sample test of, 281-283
 - sign of difference between sample means, 377
 - for standard deviation, in sequential analysis, 232-234
 - in single-sample tests of, 231, 232, 270, 271, 278-280
 - in variables inspection for fraction defective, 12, 14, 17, 33-41, 52-56, 67-71
- Acceptance inspection, 3-63, 227-234, 260n., 263, 264, 270, 271, 274, 275, 278-280, 281-283, 420-423
 - for average quality, by sequential sampling, 423
 - by single sample, 61-62
 - contrasted with quality control, 156, 157
 - definition of, 7
 - for dispersion of quality, by sequential sampling, 232-234
 - by single sample, 231, 232, 270, 271, 274, 275, 278-280
 - for fraction defective, double-sampling attributes plans, 237-244
 - compared with sequential attributes plans, 237-244
 - multiple-sampling attributes plans, 237-244

*The references are to pages. The arrangement of major topics and symbols is alphabetical; subtopics are in alphabetical order, disregarding preliminary prepositions. Greek letters are alphabetized according to their word equivalents, e.g. α as "alpha," χ^2 as "chi-squared," and ξ as "xi." Certain symbols, for example, A and a , are used in a variety of meanings; in such cases each meaning is separately listed, and the arrangement is alphabetical with respect to first word of definition given.

- Acceptance inspection, for fraction defective, multiple-sampling attributes plans, compared with sequential attributes plans, 237-244
- sequential attributes plans, 26-28, 26n., 237-244
- sequential variables plan, 83-85
- compared with single-sample variables plan, 26n., 85
- single-sample attributes plan, 26
- compared with sequential attributes plans, 26
- single-sample variables plans, 9-56
- amount of inspection, 14, 15
- compared with sequential attributes plan, 26
- compared with single-sample attributes plan, 26-28
- background of, 9-13
- based upon \bar{x} and s , 9
- conditions for advantageous use of, 9, 34
- curtailment of, 14
- efficiency of, compared with sequential attributes plan, 26
- efficiency of, compared with sequential variables plan, 26n., 85
- efficiency of, compared with single-sample attributes plan, 26-28
- operating characteristics, 15, 16, 28-33
- definition of, 14
- plan of action for, 14, 16-21
- for fraction of sample ranges less than specified limit, 227-234
- formulation in terms of σ , 229-231
- multivariate, 50-52, 156, 157
- simultaneous use of several sample criteria, 50-52, 113, 114
- single "score," 51, 113, 114
- based on generalized Student's T , 114-116
- simultaneous use of several sample criteria, 50-52, 113, 114
- for standard deviation of quality, sequential sampling, 232-234
- single-sample, 231, 232, 270, 271, 278-280
- upper and lower limits on single quality characteristic, 52-56, 63, 64
- when lot quality is measured by fraction of sample ranges that are less than specified limit, 227-234
- sequential sampling, 232, 234
- Acceptance line, 232, 356, 357, 359, 360, 422, 423, 425
- adjusting rejection line to take account of, 358-360
- figure showing, 357
- for number of "success-failure" pairs, in double-dichotomy test, 425
- for number of "successes" in binomial test, 422
- for sum of observations, in test for μ , σ known, 423
- for sum of squared deviations, in test for σ , μ unknown, 232
- of unit slope, 356, 357, 360
- (See also Acceptance criterion; Acceptance region, boundaries of)
- Acceptance number (A_k , or S_k), 237, 239, 244, 422, 425
- constant, in sequential analysis, 356
- adjusting rejection line to allow for, 358, 359
- example of, 359-361
- definition of (A_k), 237
- in double sampling, 237
- examples of, 239, 244
- infinity, 358
- in multiple sampling, 237
- examples of, 239, 244
- omitted, 358
- relation to rejection number characterizes type of sampling plan, 237
- in sequential sampling (A_k), 237
- in sequential tests (S_k), 422, 425
- in single sampling, 237, 260n., 263, 264
- Acceptance region, 36-41, 52-57, 67-71, 232, 233, 355-361, 377, 422, 423, 425
- boundaries of, for sequential binomial test, 422
- for sequential double-dichotomy test, 425
- for sequential mean test, σ known, 423
- for sequential procedure for determining whether to complete or abandon an experiment, 356-361
- figure showing, 357
- for sequential standard deviation test, μ unknown, 232-233
- for single-sample variables inspection plans for fraction defective, 35-37, 41, 53-57, 67-71
- figures showing, 38-40, 55
- for "immediate acceptance", 34, 37, 41, 67, 69-70
- determined, by constant acceptance number, 356-361
- figure showing, 357
- by pair of one-sided criteria based on \bar{x} and s , 52-54
- figure showing, 55
- by sequential-sampling procedures, 232-233, 422, 423, 425
- by sign of difference between sample means, 377
- by single one-sided criterion based on \bar{x} and s , 36-41, 67-71
- figures showing, 38-40
- by single two-sided criterion based on \bar{x} and s , 52, 54-56, 57
- figures showing, 38-40, 55, 357
- for "immediate acceptance," in variables inspection for fraction defective, 34, 37, 41, 67, 69-70
- Addition theorem, for χ^2 , 153
- Adjusted data, use of, in variables inspection for fraction defective, 36-41, 54, 69-71
- Adjusted value, of chi (χ_c), 254-255, 257
- general procedure for obtaining, 254n.
- of chi-squared (χ_c^2), 254, 255
- general procedure for obtaining, reference giving, 254n.
- of phi (ϕ_R), formula for, 401
- table of, 406
- (See also Adjustment)

- Adjustment, Bartlett's, 399
 - heuristic derivation of, 413-414
 - table to facilitate, 406
 - of chi (χ), when calculated from 2×2 table, 254, 255, 257
 - general procedure for, 254a.
 - of chi-squared, when calculated from 2×2 table, 254-255
 - general procedure for, reference giving, 254a.
 - constant (A), in graphical procedure for variables inspection for fraction defective, 36, 37, 69-71
 - optimum choice of, 4t, 54, 70, 71
 - of inverse-sine transformation, 399, 405-407, 407a.
 - heuristic derivation of Bartlett's, 413, 414
 - table to facilitate Bartlett's, 406
- of k , when N is fixed, 19, 20
- of N , by modifying OC curve, 19
- of rejection line, to allow for fixed acceptance line, 358, 359
- example, 359-361
- of s , to eliminate bias, 58
- of starting point, alter first two rounds of sequential procedure for locating a maximum, 368, 369
- Yates', 254, 255, 257
- Air testing of bombights, 113-184
 - arrangement of bombings for, 121, 122
 - function of, 117
 - multivariate quality control of, 113-184
 - problems of, 110
 - proposed sampling plan for, 119-121
- α : probability of erroneously rejecting hypothesis under test, 271, 282, 283, 419
- taken equal to 0.50, 283
- use in determining sequential test procedures, 420, 421
- (See also Error, of the first kind)
- α : probability that lot of acceptable quality will be rejected, 16
- (See also Producer's risk)
- α : true intercept of linear regression equations, 322
- estimation of, when cost of each measurement depends upon its magnitude, 322-328
- α -level of significance, 270, 278-279, 281
- Alternative hypothesis, in analysis of variance, 311-313
- for which probability of error of second kind is β , 61, 231, 260n., 263, 264, 271, 279, 313, 380, 421, 423, 424
- in tests of means, 61, 377, 379-380, 386, 423
- of proportions (percentages), 260n., 263, 264, 357-358, 421, 424
- of standard deviations (variances), 231, 270, 271, 278, 281, 311-313, 387
- American Society for Testing Materials, 58n., 93
- American Standards Association, 58n., 93
- Amount of information, about dependence of one variable on another, 321
- maximizing, when cost of each measurement depends upon its magnitude, 319-328
- Amount of information, about a function in neighborhood of maximum, 366
- provided by factorial experiment, 366, 367, 370, 371
- provided by sequential experiment, 368, 369, 370, 371
- about population mean (μ), provided by probit data, 345, 346
- maximizing, 349-352
- provided by sample mean (\bar{x}), 161
- provided by sample median, 161
- about population standard deviation (σ), provided by probit data, 345, 346
- maximizing of, 349-352
- provided by sample mean deviation, 162, 163
- provided by sample standard deviation (s), 162, 229
- about quality of lot, provided by sampling inspection, 156-158
- when inspection is by attributes, 7
- when inspection is by variables, 7
- (See also Amount of inspection)
- Amount of inspection, 14, 15, 17-21, 26-28, 60-66, 81, 82, 85, 100-109, 231, 233, 234, 235-244, 259, 260, 263, 264, 274, 275, 278, 280, 282, 283, 311-314, 319-328, 331-338, 358, 362n., 380, 381, 419, 420, 427, 428
- with attributes plans, 14, 15, 26-28, 237-244, 259, 260n., 263, 264, 427, 428
- comparison of double, multiple, and sequential sampling, 237-244
- figures showing, 240-243
- contrasted with variables plans, 26-28
- formula for determining, with sequential sampling, 427, 428
- for single sampling, 259, 260n., 263, 264
- nomogram for determining, for single sampling, 260
- method of using, 260n.
- when severity of any one test cannot be controlled precisely, 331-338
- average, 14, 15, 26, 85, 233, 234, 235-244, 358, 362n., 419, 420, 427, 428
- for comparison of two proportions, by sequential sampling, 424, 427, 428
- with curtailed (truncated) sampling, sequential, 362n.
- single, 14, 15
- for double dichotomies, by sequential sampling, 424, 427, 428
- with double sampling, compared to multiple and sequential, 237-244
- figures showing, 240, 242
- with multiple sampling, compared to double and sequential, 237-244
- figures showing, 240, 242
- with sequential analysis, contrasted with non-sequential sampling, 26, 85, 235-244, 419, 420
- general formula for one-parameter tests, 427
- with sequential attributes plans, 26, 235-244, 427, 428
- when acceptance line is omitted, 358

- Amount of inspection, average, with sequential attributes plans, contrasted with double- and multiple- sampling attributes plans, 237-244
- figures showing, 240, 242
- contrasted with single-sample attributes plans, 26
- formula for, 427, 428
- with sequential one-decision binomial test, 358, 427, 428
- with sequential one-sided binomial test, formulas for, 427, 428
- figures showing, 240, 242
- with sequential one-sided test for σ , when μ is unknown, formula for, 233
- figures showing, 234
- with sequential variables inspection plan for fraction defective, 85
- (See also ASN curve)
- when cost of each measurement depends upon its magnitude, 319-328
- in curtailed (truncated) inspection, 14, 15, 362n.
- when decisions are based on signs of differences between sample means, formula for, 380
- determination of, nomogram for, 260
- procedures for, 17-21, 27n., 28n., 64-60, 81, 82, 231, 274, 275, 278, 280, 282, 283, 311-314, 331-338, 302n., 427, 428
- for analysis-of-variance tests, 311-314
- for χ^2 -tests of variance estimates, 231, 274, 275, 278
- for curtailed (truncated) sequential sampling, 302n.
- for F-tests of variance estimates, 280, 282, 283, 296, 311-314
- for one-decision sequential binomial test, 358, 427, 428
- when severity of any one test cannot be controlled precisely, 331-338
- for standard deviation tests, 274, 275, 278, 280, 282, 283
- for variables inspection plans for fraction defective, 17-21, 27n., 28n., 84-86, 81-82
- differences in, attributes versus variables inspection, 26-28
- with double, multiple, and sequential sampling, 237-244
- figures showing, 240-243
- sequential versus non-sequential sampling, 26, 85, 237-244, 419, 420
- figures showing, 233, 240-243
- distribution of, in repeated sequential sampling, 428
- with double sampling, compared to multiple and sequential, 237-244
- figures showing, 240-243
- figures showing dependence on quality submitted, 234, 240-243
- fixed in advance, adjustment of k , 19, 20
- formulae for, 17, 27n., 28n., 60-63, 231, 233, 250, 260, 263-264, 278n., 427, 428
- in attributes inspection, with sequential sampling, 427, 428
- with single sampling, 259, 260, 263, 264
- Amount of inspection, formulas for, for binomial test, one-sided, with sequential sampling, 427, 428
- with single sampling, 259, 260n., 263, 264
- when decisions are based on signs of differences between sample means, 380
- for difference of means test, single sample, when σ is known, 61, 62
- when σ is unknown, 17, 27n., 28n., 60-66, 81, 82
- for difference of proportions (percentages) test, sequential sampling, 424, 427, 428
- single sample, 259, 260, 263, 264
- incorrect formula for, 258
- for double-dichotomy homogeneity test, 259, 260, 263, 264
- for fraction defective test based on variables, single sample, 17
- when μ is known and σ unknown, 27n., 28n., 231, 278n.
- when μ is unknown and σ known, 27n., 28n., 62
- when μ and σ are both unknown, 17, 27n., 28n., 60-63
- for general one-parameter tests, sequential sampling, 427
- single sampling, 61, 62
- for mean test, single sample, with σ known, 27n., 28n., 62
- with σ unknown, 17, 27n., 28n., 60-66, 81, 82
- for proportion test, with sequential sampling, 427, 428
- with single sample, 259, 260n., 263, 264
- when range of samples of k determines lot quality, with sequential sampling, 233
- with single sample, 231, 278n.
- for setting tolerance limits, 101, 108, 109
- for standard deviation test, with sequential sampling, 233
- with single sample, 231, 278n.
- for variables inspection plans for fraction defective, with single sample, 17
- when μ is known and σ is unknown, 27n., 28n., 231, 278n.
- when μ is unknown and σ is known, 27n., 28n., 62
- when μ and σ are both unknown, 17, 27n., 28n., 60-63
- minimum acceptable, when severity of any one test cannot be controlled precisely, 331-338
- minimum proposed, when data are coarsely grouped or rounded, 213, 214
- with multiple sampling, compared to double and sequential, 237-244
- figures showing, 240-243
- nomogram for determining, 260
- uses of, and procedures, 260
- normal, 45
- reduced, 45
- reduction in, by efficient utilization of data, 160-163
- by knowing μ or σ , 27, 28

- Amount of inspection, reduction in, by using
 double sampling, 237-244
 figures showing, 240, 242
 by using efficient formulas, 160-163
 by using multiple sampling, 237-244
 figures showing, 240, 242
 by using sequential sampling, 26-28, 85, 233,
 237-244, 369-371, 419, 420
 figures showing, 233, 240, 242
 by using variables inspection, 26-28
 with sequential sampling, 26, 26n., 85, 233-244,
 362n., 419, 420, 427, 428
 when acceptance line is omitted, 358, 358n.
 in attributes inspection, 26, 235-244, 427, 428
 contrasted with double and multiple
 sampling, 237-244
 figures showing, 240-243
 contrasted with single sampling, 26
 contrasted with non-sequential sampling,
 26-28, 85, 235-244, 419, 420
 with curtailed sampling, 362n.
 formula for, general one-parameter tests, 427
 one-sided binomial test, 427, 428
 one-sided test for σ , when μ is unknown, 233
 procedures for determining, curtailed sam-
 pling, 362n.
 general, 427
 one-decision binomial test, 358, 427, 428
 in variables inspection for fraction defective,
 85
 for setting tolerance limits, 100-108
 with single sample, 14, 15, 17-21, 26-28, 60-66,
 81, 82, 83, 231, 259, 260, 263, 264, 274, 275,
 278, 280, 282, 283, 311-314, 331-338, 380,
 381
 analysis-of-variance tests, 311-314
 attributes plans, 14, 15, 26-28, 259, 260,
 263, 264
 contrasted with sequential sampling, 26,
 419, 420
 contrasted with variables plans for
 fraction defective, 26-28
 binomial tests, one-sided, 259, 260, 260n.,
 263, 264
 χ^2 -tests of standard deviation (or variance),
 231, 274, 275, 278
 contrasted with sequential sampling, 26, 85,
 419, 420
 curtailed, 14, 15
 when decisions are based on signs of differ-
 ences between sample means, 380
 Difference of means test, when σ is known,
 61, 62
 difference of proportions (or percentages)
 test, formula, 259, 260, 263, 264
 nomogram for, 260
 double-dichotomy homogeneity tests, 259,
 260, 263, 264
 for F -tests of standard deviations (or
 variances), 280, 282, 283, 311-314
 general formula for one-parameter tests, 61-
 62
 for mean test, σ known, 27, 28, 62
 σ unknown, 17, 27n., 28n., 60-66, 81, 82
- Amount of inspection, with single sample, for
 proportion test, 259, 260n., 263, 264
 when range in samples of k determines lot
 quality, 231, 278n.
 for standard deviation tests, 231, 274, 275,
 278, 280, 282, 283
 for variables inspection plans for fraction
 defective, 17-28, 60-66, 81, 82
 when μ is known and σ unknown, 27n.,
 28n., 231, 274, 275, 278
 when μ is unknown and σ is known, 27, 28,
 82
 when μ and σ are both unknown, 17-21,
 26-28, 60-66, 81, 82
 standard deviation of, 238, 241, 243
 computational methods for determining, 244
 figures showing, 241, 243
 tables showing, for analysis-of-variance tests,
 313n.
 for attributes plans, 26
 for setting tolerance limits, 102-107
 for standard deviation tests, 272, 273, 276,
 277, 284-295, 298-309
 for variables inspection for fraction defective,
 22-27, 65
 with truncated sampling, sequential, 362n.
 single, 14, 15, 238
 variability of, 235-244
 computational methods for determining, 244
 figures showing, 241, 243
 nature of, in repeated sequential sampling, 428
- Analysis of consumption requirements, 47-49
 Analysis of experimental error (see Analysis of
 variance)
 Analysis of production possibilities, 46, 47
 Analysis of variance, 297, 310-314, 385, 386
 algebraic expression for coefficient of between-
 group variance, 312
 for degrees of freedom in, 312
 for mean squares in, 312
 expected values of, 312
 for sums of squares in, 312
 of binomial data, 398, 407, 408
 components of random variation in, 297, 310, 311
 resolution by, 311-314
 components of systematic variation, 310, 311
 components of variance, resolution by, 311-314
 of percentage data, 398, 407-408
 planning experiments leading to, 297, 310-314
 skeleton, 313
 systematic versus random variation in, 297,
 310-311
 table, 312
 tests of significance in, 312-314, 385, 386
 for components of variance, 312-314
 for differences among subgroup means, 385,
 386
 (See also Standard deviation; Variance)
- Angular difference, between two binomial prob-
 abilities, 262, 264
 between two observed proportions, 264
 Angular transformation, 257-259, 261-264, 336,
 395-416
 (See also Inverse-sine transformation)

- Animal experiments, 311, 341, 342, 343n., 352
- Applied Mathematics Panel, in, vii, x
- Summary Technical Report of, vii
- Approximations, involved in formulas for variables inspection for fraction defective, 21, 64-66
- effects of, 21, 49, 50, 62-64
- table showing, 65
- use of non-central t to avoid, 64-66
- AQL (see Acceptable-quality level)
- $\arcsin x$, reference to table of, 260n., 265, 402n., 416
- Arcsine transformation, 257-259, 261-264, 336 395-416
- (See also Inverse-sine transformation)
- Arithmetic mean, of sample measurements, 161
- as estimator of population (lot) mean, 12, 161, 162, 192, 196-198, 200, 203, 212, 213
- formula for, 12, 100, 101, 161, 192
- when measurements are grouped (or rounded), 196
- symbol for (\bar{x}), 12, 161, 192
- when measurements are grouped or rounded (\bar{x}_g), 196
- (See also Sample mean)
- Arithmetic-probability paper, 414
- Army, viii
- Arnold, Kenneth J., ix, x, xii, 6, 354, 419
- ASN (see Average sample number)
- Assignable causes, 269
- that introduce random components of variation, 297, 310, 311
- systematic components of variation, 310, 311
- Asymptotic expansion, for confidence limits for population proportion, 336
- for percentage points of t -distribution, 148
- for percentage points of T -distribution, 155
- for tolerance-limit factor K , 101
- Attributes, inspection by, 7-9, 14, 15, 26-28, 229n., 237-244, 259, 260, 263, 264, 331-338, 358-362, 419-422, 427, 428
- advantages and disadvantages of, 7-9
- amount of inspection, 14, 15, 26-28, 237-244, 259, 260n., 263, 264, 427, 428
- comparison of double, multiple and sequential sampling, 237-244
- figures showing, 240-243
- comparison of sequential and single sampling, 26, 419, 420
- comparison with variables inspection, 26-28
- formula for determining, with sequential sampling, 427, 428
- with single sample, 259, 260n., 263, 264
- nomogram for determining, with single sample, 260
- procedure for using, 260n.
- when severity of any one test cannot be controlled precisely, 331-338
- (See also Amount of inspection)
- to avoid normality assumption, 8, 229n.
- as basis for deciding whether to abandon or to complete an experiment, 355-362
- contrasted with inspection by variables, 7-9, 26-28
- Attributes, curtailment of, 14, 15, 238
- with double sampling, 237-244
- amount of inspection, average, 240, 242, 244
- variability of, 238, 241, 243, 244
- characterized by relation of R_k to A_k , 237
- computational procedures for, references to, 244
- contrasted with multiple and sequential sampling, 237-244
- formulas, for acceptance line, with sequential sampling, 422
- for amount of inspection, with sequential sampling, 427, 428
- with single sampling, 259, 260n., 263, 264
- for ASN curve, with sequential sampling, 427, 428
- for five-point OC curve, for sequential sampling, 427
- for OC curve, for single sampling, 260n., 261-263
- for rejection line, with sequential sampling, 422
- for rejection number (proportion), with single sample, 260n., 263, 264
- when inspection is costly, 9
- when inspection is destructive, 9
- with multiple sampling, 237-244
- amount of inspection, average, 240, 242, 244
- variability of, 238, 241, 243, 244
- characterized by relation of R_k to A_k , 237
- computational procedures for, references to, 244
- contrasted with double and sequential sampling, 237-244
- nomogram, for determining amount of inspection and OC curve for single sampling, 260
- procedure for using, 260n., 263
- OC curve, for sequential sampling, procedure for five-point, 427
- single sampling, formula for, 260n., 263, 264
- nomogram for, 260n., 263
- when range in samples of k determines lot quality, 229n.
- reasons for use, 7-9
- selection of AQL in, discussion of, 45-47
- with sequential sampling, 26, 235-244, 357-362, 419, 420, 421, 422, 427, 428
- acceptance line, formula for, 422
- when acceptance line is fixed in advance, 358-362
- OC curve, procedure for, 361, 362
- when acceptance line is omitted, 357, 358
- OC curve, formula for, 358
- amount of inspection, average, 26, 240, 242, 244, 419, 420, 427, 428
- variability of, 238, 241, 243, 244
- as basis for deciding whether to abandon or to complete an experiment, 357-362
- characterized by relation of R_k to A_k , 237
- computational procedures for curtailed (truncated) sampling, references to, 244, 361n., 362n.
- steps of, 361, 362

- Attributes, with sequential sampling, contrasted with double- and multiple-sampling attributes inspection, 237-244
 - contrasted with sequential variables inspection, 26n., 85
 - single-sampling, attributes inspection, 26
 - curtailed (truncated), 361, 362
- OC curve, when acceptance line is fixed in advance, procedure for, 361, 362
 - when acceptance line is omitted, formula for, 358
 - general five-point, formulas for, 427
 - when sampling is curtailed (truncated), steps in determining, 361, 362
- rejection line, formula for, 422
- when severity of any one test cannot be controlled precisely, 331-338
- with angle sample, 14, 15, 26-28, 237, 238, 259, 260n., 263, 264
 - acceptance criterion for, 260n., 263, 264
 - amount of inspection for, 14, 15, 26-28
 - contrasted with sequential-sampling attributes inspection, 26-28
 - contrasted with single-sample variables inspection, 26-28
 - formula for, 259, 260n., 263, 264
 - nomogram for, 260
 - procedure for using, 260n.
 - characterized by relation of R_s to A_s , 237
 - contrasted with double, and multiple sampling, 237
 - with sequential attributes inspection, 26
 - with single-sample variables inspection, 26-28
 - curtailed, 14, 15, 238
 - OC curve, formula for, 260n., 263, 264
 - nomograph for, 260n., 263
 - rejection criterion, 260n., 263, 264
 - when tests are destructive, 9
- Authorship, ix
- Average (see Arithmetic mean; Mean; Sample mean)
- Average error, 162
 - (See also Mean deviation)
- Average sample number (ASN, N), 238, 420
 - (See also ASN curve; Sample size, average)
- ASN curve, 233-234, 238, 240, 242, 244, 362, 427-428
 - comparison of, for double-, multiple-, and sequential-sampling attributes plans, 237-244
 - figures showing, 240, 242
 - computation of, references to general methods of, 244, 362n.
 - definition of, for general one-parameter tests, 427
 - special cases, 233, 238
 - for double-sampling attributes plans, figures showing, 240, 242
 - figures showing, 234, 240, 242
 - five point, for sequential one-parameter tests, 428
 - formulas, for general one-parameter sequential test, 427
 - ASN curve, formulas, for sequential one-sided binomial test, 427, 428
 - with acceptance line omitted, 358
 - for sequential one-sided test of σ , 233
 - maximum of, position of, 428
 - for multiple-sampling attributes plans, figures showing, 240, 242
 - formula for, 427, 428
 - for sequential attributes plans, figures showing, 240, 242
 - formula for, 427, 428
 - for sequential one-sided binomial test, figures showing, 240, 242
 - formula for, 427, 428
 - for sequential one-sided test of σ , figures showing, 234
 - formula for, 233
- Average sample size (see ASN curve; Sample size, average)
- B
- B : critical value of likelihood ratio, in sequential analysis, 420
- B : function appearing in formulae for sequential variables inspection, 84
- b : critical value of minus $\lambda(-\lambda)$ in sequential analysis, 84, 421
- b : function of N , K_α , and K_1 that appears in formula for k when N is fixed, 19, 59, 61
- formulas for, 20, 59, 61
- b : multiple of $\sigma/\sqrt{2(N-1)}$ in formula for standard deviation of s , 58
- formula for, 58
- reference to table of, 58n.
- b : ratio of standard deviation of s to $\sigma/\sqrt{2(N-1)}$, in normal samples, 58
- Baines, A. H. J., 281n., 297, 313, 314, 318
- Barlow's tables, 34, 93
- Bartlett, M. S., 183, 385, 386, 387, 393, 398, 399, 400, 401, 403-407, 411, 413-415
- Bartlett's adjustment, of inverse-sine transformation, 399
 - heuristic derivation of, 413, 414
 - table to facilitate, 406
- Bartlett's test of homogeneity of variance estimates, 183, 387, 388
 - compared to F -test for homogeneity of sample means, 386
 - as "omnibus test," 385, 386
 - optimum properties of, 386
 - separation into parts, assignable to different factors, 386
 - tables to facilitate application of, reference to, 388n.
- Bates, W. D., 193n., 218n., 222
- Bennett, Rollin F., ix
- β : probability of erroneously accepting hypothesis under test, 271, 419
 - taken equal to 0.50, 20, 21, 271, 274, 282, 283, 313, 314
 - use in determining sequential test procedures, 420, 421
 - (See also Error of the second kind)

- β : probability that lot of unacceptable quality will be accepted, 16
(See also Consumer's risk)
- β : true slope of a linear regression line, 322
estimation of, when cost of each measurement depends upon its magnitude, 322-328
- β_1 : Pearson's measure of skewness, 197, 198
- β_2 : Pearson's measure of kurtosis, 197, 198
- Beta function, incomplete-, 392, 393
percentage points of, reference to table of, 338, 394
use to determine confidence limits for population proportion, 333, 334
- Bias, of bombing errors, 137, 147, 149
of mean deviation as estimator of σ , 169a.
of p as estimator of P , 397, 410
of $\varphi(p)$ and $\varphi_B(p)$ as estimators of $\varphi(P)$, 403, 404
tables showing, 400-402
of s as estimator of σ , 58, 162
adjustment factor, formula for, 58
tables of, reference to, 58a.
of s^2 as estimator of σ^2 , 192, 199, 412
when data are grouped or rounded, 199
of sample mean as estimator of population mean, 58, 162, 197, 198
when data are grouped or rounded, 197, 198, 212, 213
of sample median as estimator of normal population mean, 162
of sample proportion as estimator of population proportion, 397, 410
when inverse-sine transformation is used, 403, 404
tables showing, 400-402
of statistical tests, if Sheppard's corrections are used, 199, 200, 203
from time trends in data, 371, 372
from use of inverse-sine transformation, 403, 404
tables showing, 400-402
from use of Sheppard's corrections, 199, 200, 203
of \bar{x} as estimator of μ , 58, 162, 197, 198
when data are grouped or rounded, 197, 198, 212, 213
of $\bar{x} + ks$ as estimator of $\mu + k\sigma$, 58
- Bigelow, Julian H., ix
- Binomial distribution, 250, 251, 421, 427
ASN curve for sequential one-sided test of parameter of, figures showing, 240, 242
formula for, 427, 428
confidence limits for parameter of, 332-336
belts giving eighty percent limits, 335
ninety percent limits, 334
ninety-five percent limits, 333
ninety-nine percent limits, 332
accuracy of, 335a.
preparation of, 335a., 336a.
sources of, 335a.
determination of, from percentage points of incomplete beta function, 333, 334
examples of, 334, 337
by using inverse-sine transformation, 336
by using non-central t -distribution, 76, 77, 336a.
- Binomial distribution, confidence limits for parameter of, formula for, for case of zero occurrences, 335, 336
relation of, to percentage points of incomplete beta function, 333, 334
design of experiments, for comparing parameters of two, 258-263, 424, 427, 428
for estimating parameter of a single, 238, 333-337
for testing parameter of a single, 259, 260a., 261-264
double dichotomies, analysis of, by means of, 249-253, 255
examples of, 251
experiments for comparing parameters of two, analysis of data from, 249-258, 424, 425
approximate single-sample method, based on binomial test, 249, 250, 255
based on x_c , 253-255, 256, 257
based on inverse-sine transformation, 257, 258, 263, 264
based on normal deviates, 253-257, 263
"exact" single-sample method for, 250-253
by Fulcher-Zubin Item Analyzer, 257, 258
incorrect method for, 250
by sequential analysis, 424, 425
by Zubin-Fulcher Item Analyzer, 257, 258
design of, 258-265, 424
inverse-sine transformation of data from, 257, 258, 263, 264, 397-408
number of observations needed, with sequential sampling, 424, 427, 428
with single samples, 258-261, 264
formula for, 258, 259, 264
nomogram for, 260
operating characteristics of (OC), 261
OC curve of, determination by formula, 262
from nomogram, 263
figure showing, 262
OC surface of, 261, 262
planning of, 258-265, 424
sequential, 424, 425
experiments for estimating parameter of a single, analysis of data from, 332-336
design of, 238, 333-337
inverse-sine transformation applied to data from, 336
number of observations needed, 333-337
sequential, 238a.
experiments for testing parameters of a single, analysis of data from, 260a., 263, 264, 421, 422
ASN curves for double, multiple, and sequential sampling, 240, 242
design of, 259, 260a., 261-264, 427, 428
inverse-sine transformation of data from, 260a., 261-264, 397-408
number of observations needed, with double sampling, 237-244
figures showing, 240-243
with multiple sampling, 237-244
figures showing, 240-243
with sequential sampling, 26, 237-244, 419, 420, 427, 428

- Binomial distribution, experiments for testing parameters of a single, number of observations needed, with sequential sampling, figures showing, 240-243
 formula for, 427, 428
 with single sampling, 14, 15, 26-28, 259, 260*n.*, 263, 264
 examples of (Table 1.3), 26
 formula for, 259, 260*n.*, 263, 264
 nomogram for, use of, 260*n.*
- OC curve of, approximate determination from formula, 260*n.*, 262
 from nomogram, 260*n.*, 263
 exact determination of points on, using confidence-belt charts, 336*n.*
 using percentage points of incomplete beta function, 334, 336*n.*
 planning of, 259, 260*n.*, 261-264, 427, 428
 sequential, 421, 422, 427, 428
 one-decision test, 358
 formula for, examples, 251
 homogeneity of samples from two, testing, 249-258, 424, 425
 (See also Binomial distribution, experiments for comparing parameters of two)
 inverse-sine transformation of data from, 257, 258, 259-264, 336, 397-408
 mean of, 397, 410
 moments of, third and fourth about mean, 410
 nomogram, for determining sample sizes, in testing parameters of, 260
 normal approximation to, 263, 264
 number of observations needed, for comparing parameters of two, 258-261, 264, 424, 427, 428
 formula for, 258, 259, 264
 nomogram for, 260
 for estimating the parameter of a single, 333-337
 for testing the parameter of a single, with double sampling, 237-244
 figures showing, 240-243
 with multiple sampling, 237-244
 figures showing, 240-243
 with sequential sampling, 26, 237-244, 419, 420, 427, 428
 figures showing, 240-243
 formula for, 427, 428
 with single sampling, 14, 15, 26-28, 259, 260*n.*, 263, 264
 examples of, 26
 formula for, 259, 260*n.*, 263, 264
 nomogram for, use of, 260*n.*
- OC curves, of tests of parameter of, 262
 one-decision test of parameter of, 358
 planning experiments for comparing parameters of two, 258-263, 424, 427, 428
 for estimating parameter of a single, 238, 333-337
 for testing parameter of a single, 259, 260*n.*, 261-264
 Poisson exponential approximation to, 426, 428
 sequential estimation of parameter of, reference to work on, 238*n.*
- Binomial distribution, sequential test, for comparing two, 424, 425
 for testing parameter of a single, 421, 422, 427, 428
 one-decision test, 358
 single sampling for comparison of two, 249-264
 for estimation of parameter of, 332-336
 for testing parameter of, 14, 15, 26-28, 259, 260*n.*, 263, 264
 standard deviation of, 255, 256, 397
 variance of, 397, 410
- Binomial-probability paper, 414*n.*
- Biological assay, 341, 342, 352
 (See also Sensitivity tests)
- Biological experimentation, 311
- Bishop, D. J., 388*n.*, 393
- Bivariate distribution, normal, 146
 relation of Hotelling's generalized T to exponent of, 114, 115
- Bliss, Chester I., 342*n.*, 343*n.*, 350*n.*, 352, 398, 400, 405, 415
- Bombsights, air testing of, function of, 117
 multivariate quality control applied to, 111-184
 problems of, 116
- Bowker, Albert H., ix, xi, 96, 101*n.*, 109
- Breaking strength, 365
 (See also Metallurgical experiments)
- Breen, Nancy Brixey, x
- Broad classes (see Grouping)
- Brown, Richard H., 343*n.*, 352
- Brown University, ix
- Bureau of the Census, ix, xi, xii, 226, 354
- Bureau of Ordnance, Navy, 352
- Bureau of Standards (see Mathematical Tables Project; National Bureau of Standards)
- ### C
- c_s : ratio of expected value of root mean square of deviations from sample mean, to σ , in normal samples, 58
 reference to tables of, 58*n.*
 relation to σ , 58*n.*
- Calculating machines, comparison of makes and models, 34*n.*
 use of, to simplify computation of s , 33, 34
- Camp-Meidell inequality, 49*n.*, 221
- Carver, H. C., 194*n.*, 222
- Causes, assignable, 369
 that introduce components of random variation, 297, 310, 311
 that introduce components of systematic variation, 310, 311
 chance, 297, 310, 311
- Cayley, Arthur, 191, 222
- Central tendency, measures of, 9
- Chance causes, 297, 310, 311
- Characteristics, operating, of sampling-inspection plans and statistical tests (see Operating characteristics, Operating-characteristic curves; Operating-characteristic surface)
- Charts, control (see Control charts)
 list of, xiv

- Check list, of possible causes of lack of control, in air testing of bombsights, 140
- of steps for calculating $k(f, t_0, e)$, 74, 75
- for calculating $K(f, j, e)$, 75, 76
- for computing OC curve, for any curtailed (truncated) sequential inspection (test) procedure, 361
- for single-sampling variables inspection plan for fraction defective, 32, 33
- for determining k , given N , p_1 , and $1 - \alpha$, 76
- given N , p_1 , and β , 76
- for determining N and k , given p_1 , p_2 , α , and β , 81, 82
- for determining p , given N , u_0 , and e , 76, 77
- for determining u_0 , given N , p_1 , and e , 76 (See also Computation)
- of general likelihood-ratio sequential test, 420, 421
- for selection of bombsights for test, and arrangement of bombings, 119-122
- of sequential procedures for locating a maximum, 367, 368
- χ : chi(x) corrected for continuity, 254
- calculation of, from observed proportions (percentages), 256, 257
- from 2×2 table, 254, 255
- significance levels of, 255
- χ^2 (chi-squared): a variable having the χ^2 -distribution, 73, 91, 270
- addition theorem for, 153
- adjusted value of, 254
- calculation of, from proportions (percentages), 256, 257
- from 2×2 table, 254, 255
- correction for continuity, 254
- significance levels of, 255
- small expected numbers, 253
- correction for continuity, general procedure for, 254n.
- distribution of, formula for, 270
- percentage points of, 108-110, 315n.
- Cornish-Fisher type expansion for, reference to, 109
- relation of K_α to, 258n.
- relation to partial sum of Poisson series, 109
- tables of, 315n.
- relation of F -distribution to, 316
- of normal distribution to, 258n.
- of s^2 -distribution to, 270, 315
- of T -distribution to, 155
- formulas for, special, 254, 256, 257
- significance levels of, 108-110, 315n.
- Cornish-Fisher type expansion for, reference to, 109
- relation to partial sum of Poisson series, 109
- tables of, 315n.
- test of homogeneity, of proportions (percentages), 256, 257
- of 2×2 table, 254, 255
- of variance estimates, 387, 388 (See also Bartlett's test)
- use in planning and interpreting experiments for testing standard deviation (or variance) estimates, 269-280
- Class interval (see Grouping interval)
- Clopper, C. J., 335n, 338
- Cochran, William G., 254n., 265, 387-389, 392, 393, 399, 407, 408, 415
- Cochran's test, for significance of largest variance estimate, 383-394
- contrasted with Bartlett's test for homogeneity of variance estimates, 386, 387
- example, worked, 388, 389
- significance levels of, tables of, 390, 391
- accuracy of, 388, 393
- computation of, method employed, 389-393
- interpolation in, method of, 388
- Coefficient, correlation, 413
- regression, estimation of, when cost of each measurement depends upon its magnitude, 322-328
- of line fitted to probit data, 343
- estimation of, 343, 344
- relation to μ and σ , 343
- of a , for setting tolerance limits (see K)
- in variables inspection for fraction defective (see k)
- Columbia University, iii, ix-xi
- Committee on War Research of, x
- Division of War Research of, vii
- Statistical Research Group of, iii, vii-x, 6, 8, 20, 26, 34, 42, 52, 83, 85, 93, 101, 108, 109, 143, 184, 188, 231, 234, 237, 244, 257, 260, 335, 358, 361, 362, 400, 405, 410, 420, 428
- Trustees of, vii
- Combination of observations, 42, 43, 113, 114, 167
- Combinations of grouping-interval widths and sample sizes satisfactory for statistical tests, 213, 214
- Combining estimates of μ , 42, 43
- of σ , 42, 43
- probabilities from statistical tests, 167, 164
- tests for, 50-52, 113-116
- effect of, on probability of acceptance, 50, 51
- into a single "score," 51, 113, 114
- based on generalized Student's T , 114-116
- values of s or s^2 , 42, 43
- values of z , 42, 43
- Comparison, of two binomial distributions, design of and analysis of data from experiments for, 247-265, 424, 425, 427, 428
- of two means, design of and analysis of data from experiments for, 61, 62
- of two percentages (or proportions), design of and analysis of data from experiments for, 247-265, 424, 425, 427, 428
- of two standard deviations (or variances), design of and analysis of data from experiments for, 267-318
- Components of variance, 269, 297, 310-314
- Compounding probabilities from statistical tests, 167
- Computation, of acceptance line, 232, 233, 356, 357, 423, 425
- acceptance number, 260n., 263, 264, 422, 425
- acceptance region, boundaries of, 36-41, 52-56, 57, 67-71, 232, 233, 422, 423, 425
- adjusted value of chi or chi-squared, 254, 255

- Computation, adjustment constant, optimum, 41, 54, 70, 71
 analysis-of-variance table, 312
 angular difference between two binomial probabilities, 264
 between two observed proportions (or percentages), 262
 arithmetic mean, 12, 100, 192
 ASN curves for, 233, 244, 362n., 427, 428
 Bartlett's adjustment, of inverse-sine transformation, 399
 Bartlett's test, of homogeneity of variance estimates, 387, 388
 bias of s as estimator of σ , 58
 of s^2 as estimator of σ^2 , when data are grouped, 199
 of $\bar{z} + k_s$ as estimator of $\mu + k\sigma$, 58
 binomial distribution, 251
 x_n from observed proportions or percentages, 256, 257
 from 2×2 table, 254, 255
 components of variance, 310-314
 confidence limits, for μ , when σ is known, 197, 198
 when σ is unknown, 99, 200-203, 213-215
 for parameter of binomial distribution, 333-336
 for population mean, 90, 197, 198, 200-203, 213-215
 for population proportion, 42, 43, 333-336
 for σ or σ^2 , 198-200, 200-203, 213-215
 control limits, for means, 147-149
 for T -statistics, 152, 153
 for variances, 151
 $\delta(f, t_0, e)$, 74, 75
 dosage-mortality curve, 342-344, 350, 352
 efficiency, of estimators of population parameters, 160-163, 227n.
 of inspection plans and statistical tests, 26-28, 85
 (See also ASN curve)
 expected frequencies, in 2×2 table, 253, 254
 h_1 and h_2 , 232, 233, 356, 357, 422, 423, 425
 K , approximate, 101, 108
 exact, 108, 109
 k , approximate, 17-19
 exact, 70-79, 81, 82
 L_p , 28-33, 50-52, 76, 77, 80, 358, 361, 427
 L_ϕ , 282-296, 316, 317
 L_p , 231, 271-279, 315
 L_σ , 232, 233
 L_T , 262, 263
 N , approximate, 17
 exact, 81, 82
 N_s , 259-260, 260n., 263, 264
 N_m , 28n., 62
 N_1 , 27n., 28n., 231, 274, 275, 278
 N_2 , 17-21, 26-28, 60-66, 81, 82
 number of observations needed, for analysis-of-variance tests, 311-314
 for attributes plans, with sequential sampling, 427, 428
 with single sampling, 259, 260n., 263, 264
 when severity of any one test cannot be controlled precisely, 331-338
 Computation, number of observations needed,
 for binomial test, one-sided, with sequential sampling, 427, 428
 with single sampling, 259, 260n., 263, 264
 for χ^2 tests of variance estimates, 231, 274, 275, 278
 for curtailed (truncated) sequential sampling, 362n.
 when decisions are based on signs of differences between sample means, 380
 for determining whether new process (product) is more (less) variable than standard, 231, 274, 275, 278
 whether one process (product) is more variable than another, 280, 282, 283, 296
 for difference of means test, when σ is known, with single sample, 61, 62
 when σ is unknown, 17, 27n., 28n., 60-66, 81, 82
 for difference of proportions test, with sequential sampling, 424, 427, 428
 single sample, 259, 260, 263, 264
 for double-dichotomy test, 259, 260, 263, 264, 424, 427, 428
 for F -tests of variance estimates, 280, 282, 283, 311-314
 for fraction-defective test based on variables, single sample, 17
 when μ is known, and σ unknown, 27n., 28n., 231, 274, 275, 278n.
 when μ is unknown, and σ known, 27n., 28n., 62
 when μ and σ are both unknown, 17-21, 27n., 28n., 60-66, 81, 82
 for general one-parameter tests, sequential, 427
 single sample, 61, 62
 for mean test, single sample, σ known, 27n., 28n., 62
 σ unknown, 17-21, 27n., 28n., 60-66, 81, 82
 for one-decision sequential binomial test, 358, 427, 428
 for proportion test, sequential sampling, 427, 428
 single sample, 259, 260n., 263, 264
 when range in samples of k determines lot quality, sequential sampling, 233
 single sample, 231, 274, 275, 278n.
 for setting tolerance limits, references to, 100, 110
 for standard deviation tests, 231, 274, 275, 278, 280, 282, 283, 296
 for variables inspection plans for fraction defective, 17-21, 27n., 28n., 64-66, 81, 82
 OC curve, for analysis-of-variance tests, 310-314
 for attributes plans, sequential sampling, 426, 427
 single sampling, 260n., 262, 263
 for binomial test, one-decision sequential, 358
 one-sided sequential, 426, 427
 truncated, 361
 one-sided single sample, 260n., 262, 263

- Computation, OC curve, for χ^2 -tests of variance estimates, 231, 232, 271-279, 315
 for comparison of two means, σ known, 61, 62
 σ unknown, 30, 59-63, 71-73, 76, 77, 80
 for comparison of two proportions or percentages, sequential, 424, 426, 427
 single sample, 262, 263
 for comparison of two standard deviations or variances, single sampling, 282-296, 316, 317
 when decisions are based on signs of differences between sample means, 378, 379
 for double-dichotomy test, 262, 263
 for F -tests of variance estimates, 282-296, 316, 317
 for fraction-defective test, based on variables, 28-33, 76, 77, 80
 for general one-parameter tests, sequential, 426, 427
 single sample, 61, 62
 for mean test, σ known, 61, 62
 for one-decision sequential binomial test, 358
 for proportion test, sequential sampling, 426, 427
 single sample, 260n., 262-263
 when range in samples of k determines lot quality, sequential, 233
 single sample, 231, 271-279, 315
 for standard deviation tests, 231-233, 271-279, 282-296, 315-317
 for variables inspection plans for fraction defective, 28-33, 76, 77, 80
 φ and φ_p , 399, 401
 $\phi(\alpha, \beta, n_1, n_2)$, 282-296, 316, 317
 R_p , for one-decision sequential binomial test, 358
 $\rho(\alpha, \beta, n)$, 231, 271-279, 315
 s or s^2 , 12, 33, 34, 162, 192
 significance levels, of Cochran's test, 389-393
 of T -distribution, 155
 of T -statistics, approximate, 155
 of t -distribution, approximate, 148
 T (angular difference), 262
 T (Hotelling's), 142, 154
 T -statistics, 131, 133, 135, 145
 $t(f, \delta, e)$, 75, 76
 tolerance limits, 97-109
 two-point estimate of μ and σ from probit data, 350
 u_0 , 76
 \bar{x} , 12, 100, 192
 yardsticks, for differences of means, 150
 for ratio of two variance estimates, 152
 for T -statistics, 156
- Computer's rule (see Rounding rule)
- Connie, L. J., 93
- Conditional probability, 41, 251
- Confidence in conclusions, 98, 269
- Confidence belts, accuracy of, 335n.
 for population proportion, 332-336
 eighty percent, 335
 ninety percent, 334
 ninety-five percent, 333
 ninety-nine percent, 332
- Confidence belts, preparation of, 335n., 336n.
 sources of, 335n.
- Confidence coefficient (γ, Γ), 43, 98, 100, 108, 332, 336
 definition of, 98
 interpretation of, 43
- Confidence intervals, 42, 43, 99, 100, 332-336
 contrasted with statistical tolerance ranges, 99, 100
 definition of, 42
 dependence of width of, on confidence coefficient, 43
 on sample size, 99, 100
 for parameter of binomial distribution, 332-336
 for population proportion, based on attributes inspection, 332-336
 based on variables inspection, 42-45
 for process-average percent defective, based on attributes inspection, 332-336
 based on variables inspection, 42, 43
 (See also Confidence belts; Confidence limits)
- Confidence limits, 99, 100, 196-203, 332-336
 contrasted with statistical tolerance limits, 99, 100
 effect of grouping (rounding) on, 192, 196-203, 213-215
 for μ , when σ is known, 197, 198
 based on grouped (rounded) data, 197, 198
 when σ is unknown, 99
 based on grouped (rounded) data, 200-203, 213-215
 for parameter of binomial distribution, 332-336
 belts giving, 332-335 (see Confidence belts)
 determination of, accurate, from percentage points of incomplete beta function, 333, 334
 examples of, 334, 337
 approximate, by means of inverse-sine transformation, 336
 by means of non-central t -distribution, 76, 77, 336n.
 formula for, accurate, for case of zero occurrences, 335
 approximate, 336
 relation of, to percentage points of incomplete beta function, 333, 334
 for population mean, 99, 197, 198
 for population proportion, 332-336
 for population standard deviation (or variance), based on rounded data, 198-200, 213-215
 (See also Confidence belts; Confidence intervals)
- Consumer's risk (β), conventional value of (10%), 46
 definition of, 16, 228, 229
 effect of reduced or tightened inspection on, 45
 maximum of, with variables inspection plans for fraction defective, 16, 17
 selection of, factors to consider in, 45-49
- Consumption requirements, analysis of, 47-49
- Contingency tables, 2×2 , 249-265, 424, 425
 (see Binomial distribution, experiments for comparing parameters of two)

- Contracts, vii
 - Control charts, applied to air testing of bomb-sights, 122-142
 - some novel features of, 119-147
 - trouble shooting with aid of, 137-140
 - Control limits, for means, 147-150
 - allowance for sampling variation of data in base period, 119, 147, 148
 - for T -statistics, 152-155
 - for variances, 151, 152
 - (See also Quality control)
 - Cornish-Fisher expansion, 109
 - Correction, Bartlett's, 399
 - heuristic derivation of, 413, 414
 - table to facilitate, 406
 - of chi or chi-squared, for continuity, 254, 255, 257
 - general procedure for, 254n.
 - factors: a , b , and c , 58
 - for grouping, Sheppard's, 193-196, 222-223
 - not to be used in connection with confidence limits or tests of significance, 199, 200, 203
 - of inverse-sine transformation, 399, 405-407, 413, 414
 - Yates', 254, 255
 - (See also Adjustment)
 - Correlation coefficient, mean of, approximate, 413
 - transformation of, to stabilize variance, 413
 - variance of, approximate, 413
 - z -transformation of, 413
 - Cost, of experiment, 269
 - of measurements dependent upon their magnitudes, 321, 322
 - linear regression analysis when, 322-328
 - Craig, Cecil C., 93, 194n., 195n., 196n., 222
 - Critical level of a normally distributed test function, derivation of, 61, 62
 - Crum, W. L., 145n., 183
 - Cumulative distribution, estimating μ and σ from data on, 339-352
 - optimum design of experiments for, 345, 346, 349-352
 - Curtailment, of sequential test, 361
 - of single-sample inspection plan for fraction defective, based on attributes, 14, 238
 - based on variables, 14
 - Curtiss, John H., 407, 410, 415
 - Curve fitting, when cost of each measurement depends upon its magnitude, 321-328
 - when data are observations on cumulative distribution, 342-352
 - when data are probits, 342-352
 - to data from sensitivity tests, 342-352
- D
- d : distance from target, 342
 - Daniels, H. E., 297n., 318
 - Data, adjusted, in variables inspection for fraction defective, 36-41, 54, 69-71
 - amount of (see Amount of inspection; N ; \bar{N} ; Sample size)
 - Data, on attributes, 7
 - bias of, 160, 371
 - combination of, 42, 43, 113-116, 167
 - correlated, 50-52, 113-116
 - on cumulative distribution, 339-352
 - grouped, 187-215
 - probit, 339-352
 - representative, 160
 - rounded, 187-223
 - selection of, reasons for random step in, 158-160
 - tabular, 215-221
 - time trends in, 371
 - transformation of, to stabilize variance, 408-413
 - on variables, 7
 - Davis, O. L., 389n., 393
 - Decimals, significant, 189n., 190n.
 - Decision function, 381, 382
 - Decisions, based on inspection by attributes, 7, 237
 - by variables, 7
 - based on sign of difference between sample means, 377
 - conditions rendering optimal, 381, 382
 - probability of being wrong, 378-380
 - figure for, 379
 - table for, 378
 - regarding largest of two or more variance estimates, 386, 387, 388, 389
 - regarding level of performance of process or product, 61, 62, 377, 423
 - regarding variability of processes (products), 231, 233, 269-271, 278, 279, 280-283
 - wrong, 271, 281, 282, 313
 - Deckinger, R. L., 335n.
 - Defective, 7
 - Degrees of freedom (f , n , v), in analysis of variance, 312
 - of χ^2 , 153, 231, 232, 270
 - division by, 12, 13, 43, 312
 - of F , 151, 281, 296, 312
 - of numerator and denominator of F to be chosen equal, 296
 - partitioning of, 312, 386
 - of s or s^2 , 12, 13, 43, 199, 203, 270, 312, 387, 388
 - of T , 155
 - of T -statistics, 145, 152-154
 - of t , 148, 203
 - non-central, 73
 - k ; a constant in numerator of non-central t , 73
 - Deming, W. Edwards, 110
 - Department, of Agriculture, 352
 - of Commerce (see Bureau of the Census; National Bureau of Standards)
 - Navy (see Bureau of Ordnance, Navy)
 - War (see Army)
 - Departures from normality, seriousness of, 49, 50, 99, 346, 377, 381
 - Derivation, of acceptance criteria, 59-63, 66-71, 263, 264, 270, 280
 - of angular transformation, 410, 411
 - of Bartlett's adjustment, 413, 414

- Derivation, of criteria for "immediate" acceptance, in variables inspection for fraction defective, 66-71
- of "exact" test for independence in 2×2 table, 250-253
- of formulas for, A (adjustment constant), 70, 71
- A (critical level), 61, 62
- adjusted value of chi or chi-squared, 254n.
- average number of observations, references to, 244
- Bartlett's adjustment, of inverse-sine transformation, 413, 414
- χ_c , 254n.
- critical level, 61, 62
- K , references to, 101, 108
- k , 59-63
- L_p , 30, 59, 61, 62
- L_T , 261, 262
- number of observations needed, 60-63, 262-264, 380
- OC curves, 30, 59, 61, 62, 261, 262
- ϕ_s , 413, 414
- $\phi(\alpha, \beta, n_1, n_2)$, 281n., 316, 317
- probability that sample means are in opposite order to population means, 378, 379
- $\rho(\alpha, \beta, n)$, 315
- tolerance-limit factor, references to, 101, 108
- two-point estimates of μ and σ from probit data, 350
- variances of, 351, 352
- variability of amount of inspection, references to, 244
- of general formulas for critical level and sample size, 81, 62
- of general transformation to stabilize variance, 408-410
- of inverse-sine transformation, 410, 411
- of logarithmic transformation of s or s^2 , 412, 413
- of optimum arrangement for estimating μ and σ from probit data, 349-352
- of optimum choice of adjustment constant, 70, 71
- of rejection criteria, 59-63, 66-71, 263, 264, 270, 280
- of square-root transformation, of a Poisson variable, 411
- of standard procedure for testing whether new process (product) is more variable than standard, 270, 271
- whether one process (product) is more variable than another, 280, 281
- of tolerance-limit factors, references to, 101, 108
- of transformation to stabilize variance, 408-410
- of variances of two-point estimates of μ and σ from probit data, 350-352
- of z -transformation of correlation coefficient, 413
- Design of experiments, 245-372
- abandoning prior to completion, with provision for, 353-362
- for air-testing bombsights, 116-122, 140-147
- analysis of variance, leading to, 297, 310-314
- for comparing two means, 61, 62, 380, 381
- Design of experiments, two proportions or percentages, 253-299, 424, 425
- two standard deviations or variances, 267-318
- when cost of any one measurement depends upon its magnitude, 319-328
- when data are observations on cumulative distribution, 339-352
- when data are probits, 339-352
- when decisions are based on signs of differences between sample means, 377-382
- for determining existence of components of random variation, 297, 310-314
- for determining maximum of a function, 363-372
- for determining whether level of performance of new process (product) exceeds standard, 17, 27n., 28n., 60-66, 81, 82, 423
- whether level of performance of one process (product) exceeds that of another, 61, 62
- whether variability of new process (product) exceeds standard, 269-278
- is less than standard, 278-280
- where variability of one process (product) exceeds variability of another, 280-296
- for dosage-mortality studies, 339-352
- for estimating components of variance, 297, 310-314
- factorial, 356, 366, 367, 369-372
- failure of equipment, with provision for rate of, 355
- when independent variable is known only in terms of a probability distribution, 331-338
- for maximum of a function, 363-372
- for probit data studies, 339-352
- for proofing gun barrels, 331-338
- randomization in, 141, 371
- rate of failure of equipment, provision for, in, 355
- replication in, 141, 159
- for sensitivity tests, 339-352
- sequential, 417-429
- for determining maximum of a function, 367-372
- when rate of failure of equipment is high, 353-362
- when severity of any one test cannot be controlled precisely, 331-338
- Designs (*see* Experiment designs)
- Destructive tests, 9, 321, 331, 341
- Deviate (*see* Normal deviate)
- Deviation (*see* Mean deviation; Standard deviation)
- Differences between means, acceptance criterion for non-significance of, σ known, 61, 62
- σ unknown, 71, 72, 150
- analysis-of-variance test of significance of, 385, 386
- design of experiments when decisions are to be based on, 61, 62, 377-382
- effect of grouping or rounding on test of, σ known, 196-198
- σ unknown, 200-203, 214, 215

- Differences between means, F -test of, 385, 386
 number of observations needed for test of, σ
 known, 61, 62
 σ unknown, 71-73, 81, 82, 150
 one-sided test, σ known, sequential, 423
 single sample, 61, 62
 σ unknown, sequential, 71, 83-85, 426
 single sample, 71, 72
 sequential test of, σ known, 423
 σ unknown, 71, 72, 83-85, 426
 signs of, basis for decisions, 377-382
 t -test of, sequential, 71, 72, 83-85, 426
 single sample, 71, 72, 81, 82, 150
 two-sided test, σ known, 61, 62, 426
 σ unknown, 150, 426
 yardsticks for, 150
- Differences between proportions or percentages,
 acceptance criteria for non-significance of,
 251-255, 263, 264, 424, 425
 angular representation of, 262, 264
 design of experiments for testing, 258-265, 424,
 425
 number of observations needed for test of, 262-
 264
 sequential test for, 424, 425
 single-sample test, approximate methods for,
 249, 250, 253-257, 263
 "exact" method, 250-253
 Fulcher-Zubin Item Analyzer, 257, 258
 incorrect method, 256
 (See also Binomial distributions, experiments
 for comparing parameters of two)
- Digits, significant, 189*n.*, 190*n.*
- Discontinuities of sampling distributions, result-
 ing from grouping data, 203-218
- Discriminant function, best, for discriminating be-
 tween two populations of known form, 381,
 382
- Discriminating power of experiment, 269
- Dispersion, measures of (see Mean deviation;
 Range; Standard deviation)
- Distribution, of adjusted value of chi (χ_a), 255
 of amount of inspection, with double, multiple,
 and sequential sampling, 235-244
 computational methods for determining, 244
 figures showing, 241, 243
 nature of, in repeated sequential sampling,
 428
 of angular difference between two proportions
 or percentages, 263, 264
 of arithmetic mean, 197, 198
 when data are grouped, 196-198, 203, 212,
 213
 of average error, 162, 163
 of Bartlett's test for homogeneity of variance
 estimates, 387, 388
 beta function, incomplete, 333, 334, 338, 392-
 394
 binomial, 250, 251, 421, 427
 bivariate normal, 146
 of chi, corrected for continuity (χ_c), 255
 of chi-squared (χ^2), formula for, 270
 percentage points of, 108-110, 258*n.*, 315*n.*
 relation to F -distribution, 316
 Distribution, of chi-squared (χ^2), relation to
 normal distribution, 258*n.*
 to π^2 -distribution, 270, 315
 to T -distribution, 155
 of Cochran's test for significance of largest vari-
 ance estimate, 389, 392, 393
 of correlation coefficient, 413
 cumulative, 339-352
 Error (see Normal distribution)
 of error of an interpolated value, 221
 of F , formula for, 281
 relation to chi-squared distribution, 316
 to incomplete beta function, 392, 393
 significance levels of, 394
 detailed references to, 317*n.*
 Paulson's approximation, 393, 394
 when data are rounded, 214, 215
 Gaussian (see Normal distribution)
 generalized normal, 197
 (See also Gram-Charlier series)
 of generalized Student ratio (T), 155
 of Hotelling's T , 155
 J -shaped, 194, 222
 kurtosis of a , measures of, 197, 198
 of mean (see Distribution of arithmetic mean)
 of mean deviation, 162, 163
 of median, 162
 moments of, about origin, 193
 about true mean, 195
 centroidal, 195
 effect of grouping or rounding on, 193-196
 ideal, 193
 realistic, 193
 of N , in double, multiple, and sequential sam-
 pling, 235-244
 computational methods for determining, 244
 figures showing, 241, 243
 nature of, in repeated sequential sampling,
 428
 non-central t , 8*n.*, 22, 64, 71-82
 use in variables inspection for fraction defect-
 ive, 71-82
 non-normal, 99, 381
 normal, figure showing, 10
 formula for, 161
 (See also Normal distribution)
 Poisson, 411, 412, 426
 relation to χ^2 distribution, 109
 of proportions or percentages, 250, 251, 263,
 264, 397
 (See also Binomial distribution)
 of r , 413
 of range, 229, 230, 234
 rectangular, 195, 214, 215
 of s or s^2 , 58, 199
 when data are grouped or rounded, 198-200,
 203, 204
 relation to χ^2 distribution, 270, 315
 semi-invariants of, 196*n.*
 skewness of, measures of, 197, 198
 of Student's t , 201, 202
 when data are grouped or rounded, 200,
 203, 214, 215

- Distribution, of Student's t , 187, 188, 200
 of T , 154, 155
 relation to χ^2 distribution, 155
 relation to F -distribution, 155
 of T -statistics, 152-155
 of t , 72, 148
 effect of grouping or rounding on, 200-203,
 214, 215
 non-central, 8n., 22, 64, 71-82
 percentage points of, 148, 148n.
 of variance ratio (F), formula for, 281
 relation to χ^2 -distribution, 316
 to incomplete beta function, 302, 393
 significance levels of, 394
 detailed references to, 317n.
 Paulson's approximation, 393, 394
 when data are grouped or rounded, 214-215
 of z , 197, 198
 when data are grouped or rounded, 196, 198,
 203, 212, 213
- Division of War Research, Columbia University,
 vii
- Dodge, Harold F., 8n., 93
- Dosage-mortality curve, 342, 343n., 352
 design of experiments for determining, 339-352
- Double dichotomy, analysis of data in form of,
 sequential, 424, 425
 single sample, 250-258
 approximate method (χ_0), 253-255
 "exact" method, 250-253
 design of experiments leading to, 258-265
 number of trials needed, 258-261
 formula for, 259, 260
 nomogram for, 260
- operating characteristics (OC) of single-sample
 test, 261
- OC curve, figure for, 263
 formula for, 262
- OC surface, 261, 262
- sequential analysis applied to, 424, 425
- Double sampling, attributes inspection for frac-
 tion defective, 237-244
 average amount of inspection, compared to
 multiple and sequential sampling, 238-249
 computational methods for, references to, 244
 figures showing, 240, 242
 characterized by relation of rejection number
 (R_k) to acceptance number (A_k), 237
 variability of amount of inspection [$\sigma(N)$], com-
 pared to multiple and sequential sampling,
 238-244
 computational methods, references to, 244
 figures showing, 241, 243
- Dwyer, Paul S., 172n., 183
- E
- Economic time series, 177
- Efficiency, of sample statistics as estimators of
 population parameters, 227n.
 arithmetic mean as estimator of μ , 162
 when data are grouped or rounded, 197
 mean deviation as estimator of σ , 163
- Efficiency, of sample statistics as estimators of
 population parameters, median as esti-
 mator of μ , in normal samples, 162
 range as estimator of σ , 227
 s as estimator of σ , 162, 227
- of sampling-inspection plans and procedures,
 attributes versus variables, 26-28
- double sampling, versus multiple and sequen-
 tial, 237-244
- multiple sampling, versus double and sequen-
 tial, 237-244
- sequential sampling, versus non-sequential,
 26, 85, 237-244, 419, 420
- single sampling, versus sequential, 26, 85,
 419, 420
- of statistical tools, 386n., 394
- Eisenhart, Churchill, in, ix-xii, 186, 268, 376, 384,
 390
- Elderton, W. Palin, 194n., 222
- Enumeration data (*see* Attributes; Binomial dis-
 tribution; Poisson distribution)
- e : probability of acceptance, 59
- ϵ : probability that a normal deviate will exceed
 $K\epsilon$, 17
- Error, average, 162
 (See also Mean deviation)
 components of, 269, 297, 310-314
 of first kind, 271, 281, 282
 grouping of, 187-189, 195, 218, 222
 of interpolated value, 218, 219, 222
 of measurement, 188, 189
 probable, 187n., 223
 random, 269, 297, 310
 of second kind, 271, 281, 282
 at standard (*see* Standard deviation)
 systematic, 222, 310
 of tabular value, 215-218, 221
- Estimate, statistical use of the term, 12
- Estimation, abandoned prior to completion, 355,
 356
 by confidence intervals, 42, 43, 99, 100, 332-336
 effect of grouping or rounding on, 192, 196-
 203, 213-215
 of fraction defective, by attributes inspection,
 332-336
 by variables inspection, 42, 43, 58
 of maximum of a function, 363-372
 of $\mu + k\sigma$, by $\bar{x} + ks$, 58
 of population mean (μ), from probit data (ob-
 servations on cumulative distribution), 343,
 350
 by sample mean, 12, 58, 161, 162, 192
 effect of grouping or rounding on, 187, 188,
 196-198, 200, 203, 212, 213
 by sample median, 161, 162
 from sensitivity data, 343, 350
 of population proportion (P), by confidence
 belts, 332-336
 by sample proportion (p), 397, 410
 from transformed proportion (ϕ), 403, 404
 of population standard deviation (σ), from pro-
 bit data (observations on cumulative dis-
 tribution), 343, 350
 from mean deviation, 162, 163, 169

- Estimation of population standard deviation (σ),
 from s , 12, 58
 of population variance (σ^2), by mean deviation,
 162, 163, 169
 by s^2 , 162
 when data are grouped or rounded, 198-
 200, 212-214
 sequential, reference to, 238n.
 of slope and intercept of regression line, when
 cost of each measurement depends upon its
 magnitude, 319-328
 when probit data are involved, 343
 of statistical tolerance limits, 97-110
 "Exact" method, for analyzing 2×2 table, 250-
 253
 Expected value, 397, 408
 of mean deviation, in normal samples, 169
 of p , in binomial samples, 397, 410
 of $\phi(p)$ and $\phi_g(p)$, 403, 404
 tables giving, 400-402
 of range, in normal samples, 227n.
 of s , in normal samples, 58
 of s^2 , 192, 412
 when data are grouped or rounded, 199, 212,
 213
 of \bar{x} , arbitrary population, 197, 198
 when data are grouped or rounded, 197, 198
 of $\bar{x} + ks$, 58
 Experiment designs, factorial, 356, 366, 367, 369-
 372
 definition of, 366n.
 problems for which ideally suited, 366
 sequential, 417-429
 for determining maximum of a function, 367-
 372
 when failure rate of equipment is high, 353-
 362
 (See also Sequential analysis; Sequential-
 sampling-inspection plans)
 Experimental method, compared to standard
 method, 250
 Experimentation, when cost of each measurement
 depends upon its magnitude, 319-328
 when failure rate of equipment is high, 353, 356
 when measurements are observations on cumu-
 lative distribution, 339-352
 role of randomization in, 141, 142, 160
 role of replication in, 159
 when severity of any one test cannot be con-
 trolled precisely, 331-338
 (See also Design of experiments; Experiment
 designs; Experiments)
 Experiments, abandoning prior to completion,
 provision for, 355, 356
 for ammunition-proofing of gun barrels, 331-338
 metallurgical, 321
 (See also Design of Experiments; Experi-
 mentation; Experiment designs)
 Extreme observations, 234
 F
 F: the variance ratio, or any random variable
 having the variance-ratio distribution, 151,
 152, 155, 281
 F: the variance ratio, analysis of variance, uses
 in, 311-314
 definition of, customary, ambiguity of, 151n.
 general, 281
 for grouped or rounded data, 215
 degrees of freedom ($n_1, n_1; n_2, n_2$), ambiguity re-
 garding, 151n.
 unambiguous specification of, 281
 distribution of, formula for, 281
 percentage points, Paulson's approximation,
 393, 394
 relation to percentage points of χ^2 -dis-
 tribution, 316
 Fisher's z , 317n.
 incomplete beta function, 392, 393
 tables of, references, 151n., 184, 317n., 318
 comments on, 151n., 152n., 317n.
 distribution of log F , when degrees of freedom
 are equal, 152
 e^2 , 317n.
 formulas for, general, 281
 for grouped or rounded data, 215
 special, 151, 160
 relationship to χ^2 , 215, 281, 316
 to Fisher's z , 317n.
 of Hotelling's T^2 to, 155
 to incomplete beta function, 392, 393
 significance levels of, Paulson's approximation,
 393, 394
 relation to significance levels of χ^2 -distribu-
 tion, 316
 of incomplete beta function, 392, 393
 tables of, references to, 151n., 184, 317n.,
 318n.
 comments on, 151n., 152n., 317n.
 test of homogeneity of sample means, 385, 386
 compared to Bartlett's test for homogeneity
 of variance estimates, 386
 discriminating power of, improved by parti-
 tioning comparisons, 386
 as "omnibus" test, 386
 test of ratio of two variance estimates, 280-318
 use in planning and interpreting experiments
 for comparing two standard deviation or
 variance estimates, 280, 283, 296
 for detecting presence of components of
 variance, 311-314
 for determining whether one process (prod-
 uct) is more variable than another, 280-
 283, 296
 $F(N)$: any function of N that is independent of σ ,
 61
 f: degrees of freedom of chi-squared (χ^2), 75
 Factorial design, of experiments, 356, 366, 367,
 369-372
 definition of, 366n.
 situations for which ideal, 366
 Factorials, in "exact" analysis of 2×2 table,
 251-253
 logarithms of, reference to tables of, 253n.
 Failure of equipment, allowance for rate of, in
 planning experiments, 355-362
 Ferris, C. D., 318n.
 Fiducial limits (see Confidence limits)

- Figures, list of principal, xiv
 Fire-control devices, 249
 Fisher, Ronald A., 18, 93, 109, 116, 120n., 149n., 151, 152n., 159n., 163n., 167, 177n., 183, 192n., 197, 200, 201, 203, 211n., 212, 218, 219n., 220, 221, 222, 232, 234, 250n., 255, 258n., 265, 270n., 297, 315n., 317n., 318, 325n., 328, 342n., 343n., 352, 366n., 372, 398, 399, 400, 405, 407, 413, 414n., 415
 Fisher-Cornish type of expansion, 109
 Five-point OC curve, 28-30, 427
 Flatness of probability distribution (*see* Kurtosis)
 Forman, H. Irving, x
 Formula, for A (adjustment constant), 41, 54, 70, 71
 A (critical value of likelihood ratio), 420
 A (critical value of normally distributed test function), 62
 A (function in formulas for sequential variables plan for fraction defective), 84
 A_k , in terms of R_k , 237
 a (critical value of h in sequential analysis), 84, 420
 a (multiple of σ in formula for mean of a), 58
 acceptance criterion, in analysis of variance, 312, 313
 for difference of means, 61, 62
 for difference of proportions, 263, 264
 general, in sequential analysis, 420
 with (large) single sample, 61, 62
 for mean, in sequential test, 423
 in single-sample test, 61, 62
 for proportion, in sequential test, 422
 in single-sample test, 260n., 264
 when range in samples of k determines lot quality with single sample, 229, 232
 for ratio of two variance estimates, 281, 283
 for s^2 , in single-sample test, 232, 270, 279
 in variables inspection for fraction defective, 12, 33-35, 37, 41, 69-71
 acceptance line, for number of "successes," in binomial test, 422
 for number of "success-failure" pairs, in double-dichotomy test, 425
 for sum of observations, in test for μ , with σ known, 423
 for sum of squared deviations, in test for σ , with μ unknown, 232
 adjusted value of chi (χ_a), 254, 257
 adjustment constant (A), 41, 54, 70, 71
 adjustment of k , N fixed, 19, 20
 amount of inspection, attributes plan, sequential sampling, 427, 428
 single sample, 259, 260n., 263, 264
 binomial test, one-sided, sequential sampling, 427, 428
 single sample, 259, 260n., 263, 264
 when decisions are based on signa of differences between sample means, 380
 difference of means test, σ known, 61, 62
 σ unknown, 17, 27n., 28n., 60-66, 81, 82
 difference of proportions test, 259, 260, 263, 264
 Formula, amount of inspection, double-dichotomy test, 259, 260, 263, 264
 fraction defective test based on variables, 17
 when μ is known and σ unknown, 27n., 28n., 231, 278n.
 when μ is unknown and σ known, 27n., 28n., 62
 when μ and σ are both unknown, 17, 27n., 28n., 60-63
 general one-parameter sequential tests, 427
 single-sample tests, 61, 62
 mean test, σ known, 27n., 28n., 62
 σ unknown, 17, 27n., 28n., 60-66, 81, 82
 proportion test, sequential sampling, 427, 428
 single sample, 259, 260n., 263-264
 when range in samples of k determines lot quality, sequential sampling, 233
 single sample, 231, 278n.
 standard deviation test, sequential sampling, 233
 single sample, 231, 278n.
 variables inspection plans for fraction defective, 17
 when μ is known and σ is unknown, 27n., 28n., 231, 278n.
 when μ is unknown and σ is known, 27n., 28n., 62
 when μ and σ are both unknown, 17, 27n., 28n., 60-63
 analysis-of-variance table, entries of, 312
 angular difference, between two binomial probabilities, 262, 264
 between two observed proportions, 264
 angular transformation, 258, 398, 399
 modified, 401
 arithmetic mean, 12, 100, 101, 192
 asymptotic, for confidence limits for population proportion, 336
 for percentage points of T -distribution, 155
 for percentage points of t -distribution, 148
 for tolerance-limit factor K , 101
 ASN curve, for general one-parameter sequential tests, 427
 for sequential one-sided binomial test, 427, 428
 with acceptance line omitted, 358
 for sequential one-sided test of σ , 233
 b (critical value of $-\lambda$ in sequential analysis), 84, 421
 b (function that appears in formula for k when N is fixed), 20, 59, 61
 b (multiple of $\sigma/\sqrt{2(N-1)}$ in formula for standard deviation of a), 58
 Bartlett's adjustment, of inverse-sine transformation, 399
 Bartlett's test of homogeneity of variance estimates, 387, 388
 beta function, incomplete, 392
 binomial distribution, 251
 boundaries of acceptance and rejection regions, sequential binomial test, 422
 sequential double-dichotomy test, 425
 sequential mean test, σ known, 423

- Formula, boundaries of acceptance and rejection regions, sequential procedure for determining whether to complete or abandon an experiment, 356-361
 sequential standard deviation test, μ unknown, 232, 233
 single-sample variables inspection plans for fraction defective, 35-37, 41, 53, 54, 56, 57, 67-71
- c_2 , 58
 χ_0 , 254
 χ^2 , 254, 256, 257
 χ^2 -distribution, 270
 Cochran's test for significance of largest variance estimate, 388
 approximate significance levels of, 392
 confidence limits, for parameter of binomial distribution, 335, 336
 control limits, for means, 147-148
 correlation coefficient, transformation of, 413
 critical level (λ) of normally distributed test function, 62
 degrees of freedom, in analysis of variance, 312
 of T , 155
 of T -statistics, 145, 152-154
 $\delta(f, g, e)$, 74
 for estimating variance of linear regression fitted by weighted least squares, 343
 expected frequencies, in 2×2 table, 253
 expected value, of mean deviation, in normal samples, 169
 of p , in binomial samples, 397, 410
 of s , in normal samples, 58
 of s^2 , arbitrary population, 197, 198
 when data are grouped or rounded, 199
 of \bar{x} , 197, 198
 of $\bar{x} \pm ks$, 58
 F , general, 281
 for grouped or rounded data, 215
 special, 151, 169
 γ_1 , 198
 γ_2 , 198
 general transformation to stabilize variance, 409
 generalized Student ratio (T), 154, 155
 h_1 and h_2 , 232, 233, 356, 357, 422, 423, 425
 Hotelling's T , 154, 155
 interpolated value, error of, 219
 variance of, 219, 220
 interpolation without differences, 219
 inverse-sine transformation, 258, 398, 399
 modified, 410
 K , 101, 108
 K_a , 263
 K_b , 263, 264
 K_c , 17, 18, 31, 260
 k , 17, 19, 59, 60, 63, 81, 82
 kurtosis, measures of, 197, 198
 L_p , 30, 51
 L_σ , 232, 233
 L_r , 262
 Lagrangian interpolation coefficients, 219
 m , 350
 mean (see Formula, arithmetic mean)
- Formula moments, of arbitrary distribution, 193
 when data are grouped or rounded, 193, 195
 average, 194
 of distribution of s^2 , grouped and ungrouped data, 199
 of t , grouped and ungrouped data, 199
 of \bar{x} , grouped and ungrouped data, 198
 N (number of observations needed in each of two samples), 259, 264, 380
 N (number of observations needed in single sample), 17, 26, 28, 60-62, 72, 73, 81, 231, 259, 260n., 264, 278n.
 \bar{N} , 233, 427, 428
 N_a , 26, 259, 260n., 264
 N_m , 28n., 61, 62
 N_n , 28n., 231, 278n.
 N_s , 17, 28n., 60, 61, 81
 non-central t , 72, 73
 normal distribution, 17, 18, 31, 161, 260, 263, 423
 number of observations needed, with attributes inspection, sequential sampling, 427, 428
 single sample, 259, 260n., 264
 binomial test, one-sided, sequential sampling, 427, 428
 single sample, 259, 260n., 264
 χ^2 test of variance estimate, 231, 278n.
 when decisions are based on signs of differences between sample means, 380
 for determining whether level of performance of a process (product) exceeds standard, 17, 28n., 60-62, 81
 whether variability of performance of a process (product) exceeds standard, 231, 278n.
 difference of means test, single sample, σ known, 61, 62
 σ unknown, 17, 28n., 60, 61, 81
 difference of proportions test, sequential sampling, 424, 427, 428
 single sample, 259, 260, 263, 264
 double-dichotomy test, sequential sampling, 424, 427, 428
 single sample, 259, 260, 263, 264
 fraction defective test based on variables, 17
 μ known, σ unknown, 28n., 231, 278n.
 μ unknown, σ known, 28n., 61, 62
 μ and σ unknown, 17, 28, 60, 61, 81
 general one-parameter tests, sequential sampling, 427
 single sample, 61, 62
 mean test, single sample, σ known, 28n., 61, 62
 σ unknown, 17, 28n., 60, 61, 81
 proportion test, sequential sampling, 427, 428
 single sample, 259, 260n., 264
 when range in samples of k determines lot quality, sequential sampling, 233
 single sample, 231, 278n.
 for setting tolerance limits, references to, 109, 119
 standard deviation test, sequential sampling, 233
 single sampling, 231, 278n.

- Formula, number of observations needed, variables inspection plans for fraction defective, 17
- μ known, σ unknown, 28n., 231, 278n.
 - μ unknown, σ known, 28n., 61, 62
 - μ and σ unknown, 17, 28n., 60, 61, 81
- OC curve, for analysis-of-variance tests, 313
- attributes inspection, single sample, 260n., 262
 - binomial test, one-decision, sequential, 358
 - one-sided, single sample, 260n., 262
- χ^2 test of variance estimate, 231, 232, 271, 278n., 279, 315
- when decisions are based on signs of differences between sample means, 370
 - difference of means test, σ known, 61-62
 - σ unknown, 30, 59-61, 62, 63, 72, 73
 - difference of proportions test, single sample, 262
 - double-dichotomy test, single sample, 262
 - experiments for determining whether level of performance of one process or product exceeds standard, 30, 59-63, 72, 73
 - whether variability of one process or product exceeds standard, sequential sampling, 233
 - single sample, 231, 232, 271, 278n., 279, 315
 - whether variability of one process or product exceeds variability of another, 282, 316
- F-tests of variance estimates, 282, 313, 316
- fraction defective test based on variables, 30, 59-63, 72, 73
 - general one-parameter tests, single sample, 61, 62
 - mean test, single sample, σ known, 61, 62
 - σ unknown, 30, 59-61, 62, 63, 71-73, 76, 77
 - one-decision sequential binomial test, 358
 - proportion test, single sample, 260n., 262
 - when range in samples of k determines lot quality, sequential sampling, 233
 - single sample, 231, 232, 271, 278n., 279, 315
 - standard deviation tests, 231, 232, 271, 278n., 279, 282, 313, 315, 316
 - variables inspection for fraction defective, 30, 59-63, 72, 73
- φ and φ_s , 399, 401
- ϕ (α, β, n_1, n_2), 282, 316
- probability that sample means will be in opposite order to population means, 379
- probit, variance of z , 350
- R_p , for one-decision sequential binomial test, 358
- r , transformation of, 413
- ρ (α, β, n), 231, 232, 271, 278n., 279, 315
- s (slope of decision line, in graphical procedure for sequential tests), 233, 358, 422, 423, 425
- s or s^* , 12, 43, 162, 192
- sample size (see Formula, number of observations needed)
- significance levels of Cochran's test, 392
- of T -distribution, 155
 - of t -distribution, 148
- standard deviation, of observed proportion, 255, 397
- Formula, standard deviation, of mean, 58
- of s , in normal samples, 58
 - of \bar{s} , 258
 - of \bar{x} , 58
 - of $\bar{x} + ks$, in normal samples, 58
 - (See also Formula, variance)
- Student's t , 200
- Student's z , 187n.
- T (angular difference between two binomial probabilities), 262, 264
- T (Hotelling's), 142, 154
- T -statistics, 131, 133, 135, 145
- t (angular difference between two observed proportions), 264
- t (Student's), 200
- non-central, 72, 73
- t (f, d, c), 74
- tolerance-limit factor (K), 101, 108
- two-point estimates of μ and σ from probit data, 350
- variance of, 351, 352
- transformation to stabilize variance, 409
- (See also Inverse-sine transformation; z -transformation)
- variance, of angular difference between two observed proportions, 264
- arithmetic mean, 162
- when data are grouped or rounded, 198
- binomial distribution, 397, 410
- correlation coefficient, 413
- "error" due to grouping or rounding, 195, 218
- grouped or rounded variable, 195
- interpolated value, 219
- mean, 162
- when data are grouped or rounded, 198
- median, 162
- φ and φ_s , 400, 407
- Poisson distribution, 411
- probit, 350
- proportion, 397, 410
- r , 413
- s^* , arbitrary population, 199
- when data are grouped or rounded, 199
- t (angular difference between two observed proportions), 264
- θ (transformed proportion), 400
- two-point estimates of μ and σ from probit data, 351, 352
- z , 162, 198
- variance estimates, 12, 43, 162, 192
- z , 12, 43, 100, 192
- yardsticks, for differences of means, 150
- Fourfold table (see Double dichotomy)
- Fraction defective, definition of, 10
- dependence upon μ and σ of items in lot, 10
 - as measure of lot quality, 11, 42
 - (See also Acceptance in pecton, for fraction defective)
- Frankel, Lester, 149n., 155n., 184
- Freedom, degrees of (see Degrees of freedom)
- Freeman, Harold A., ix, 419n., 428
- Frequencies, expected, in 2×2 table, 253
- Frequency distributions (see Distribution)

- Friedman, Milton, ix, xi, xii, 6, 320, 340, 364, 419n.
- Fry, Thornton C., 253n., 265
- Fulcher, John S., 257n., 265
- Fulcher-Zubin Item Analyzer, 257, 258
- Function, experimental determination of
maximum of, 383-372
- G
- Γ : confidence coefficient associated with confidence belts for parameter of binomial distribution, 335, 336
- γ : a confidence coefficient, 42, 43, 98, 100, 103, 332, 336
- γ_c : confidence coefficient used in judging whether to continue normal inspection, 44
- γ_r : confidence coefficient used in judging whether to resume normal inspection, 44
- γ_1 : Fisher's measure of skewness, 197, 198
- γ_2 : Fisher's measure of kurtosis, 197, 198
- Gamma distribution (see Chi-squared distribution)
- Gaussian distribution (see Normal distribution)
- Geary, R. C., 201, 222
- General one-parameter tests, sequential sampling, 426-428
- single sampling, 61, 62
- General transformation to stabilize variance, 409
- Generalized normal curve, 197
- (See also Gram-Charlier series)
- Generalized Student's ratio (T), definition of, 142, 154, 155
- distribution of, 154, 155
- asymptotic expansion for percentage points of, 155
- free from nuisance parameters, 115
- relation to χ^2 -distribution, 155
- to F -distribution, 155
- optimum properties of, 147
- as "score," combining results of two or more tests, 113-116
- Generalized variance, 166
- Girshick, Meyer A., ix, xi, xii, 6, 226, 238n., 244, 354, 419
- Glaisher, J. W. L., 191, 222
- Glossary for Chap. 1, 85-92
- Goldberg, Henry, x, 83n., 109, 149n., 184
- Gosset, William Sealy, 187
- (See also Student)
- Gram-Charlier series, 197
- Graphical procedure, for analyzing binomial data, 260-262
- binomial-probability paper, reference to, 414
- nomogram for, 260
- Zubin's, 416
- for determining whether to abandon or complete an experiment, 350-359
- worked example, 350-361
- in sequential analysis, binomial test, one-decision, 358
- one-sided, 422
- comparison of two proportions, 425
- double-dichotomy test, 425
- mean test, σ known, 423
- proportion test, 422
- Graphical procedure in sequential analysis, standard deviation test, μ unknown, 232, 233
- in variables inspection for fraction defective, 34-37, 41
- adjustment constant (A), 36, 37, 40, 60-71
- optimum choice of, 41, 54, 70, 71
- advantages of, 36
- boundaries of acceptance and rejection regions, figures showing, 38-40
- formulas for, 35-37, 41
- derivation of, 66-71
- impossible region, indicating a mistake, 36, 37
- figures showing, 38-40
- when upper and lower limits on a single quality characteristic define acceptable quality, 52-56
- one two-sided criterion, 54-57
- pair of one-sided criteria, 53, 64
- Grouped data, impossibility of avoiding use of, 187, 188, 189
- Grouping (of data), 187, 188, 191-215
- effect of, on descriptive statistics, 187, 188
- on distribution of F , 214, 215
- of s^2 , 198-200, 203-214
- of t , 200-203, 214, 215
- of \bar{x} , 196-198, 212, 213
- on estimation, of population mean, 197, 198, 200-203
- population variance, 198-200, 203-214
- on moments, 193-196
- representation as effect of a random grouping or rounding error, 195, 218
- on standard procedures of statistical inference, 191-215
- with large samples, 191-203
- with small samples, 203-215
- impossibility of avoiding, 187, 188, 189
- reasons for, 187
- Grouping interval, recommended choice of size of, 192, 214
- Grouping lattices, effect of position of, on distribution of s^2 , 206-213
- on distribution of \bar{x} , 212, 213
- on estimation of μ and σ^2 by \bar{x} and s^2 , respectively, 212, 213
- random location of, 194
- extends validity of Sheppard's corrections, 196
- when only non-negative observations can occur, 196
- Groups, variation within and between, 312
- Grubbs, F. E., 318n.
- Gun barrels, pressure proofing of, 331-338
- H
- h : number of lots from which samples are taken and combined for computing process average, 42
- h_1 : negative of intercept of lower decision line (acceptance line) in graphical procedure for sequential tests, 426
- formula, for binomial test, one-sided, 422
- double-dichotomy test, 425
- mean test, σ known, 423

- A_1 : negative of intercept of lower decision line (acceptance line) in graphical procedure for sequential tests, formula, standard deviation test, μ unknown, 233
 taken equal to infinity, to provide for rejection only, 358
 use in constructing five-point OC curve, 427
- A_2 : intercept of upper line (rejection line) in graphical procedure for sequential tests, 426
 formula for, binomial test, one-decision, 358
 one-sided, 422
 double-dichotomy test, 425
 mean test, σ known, 423
 standard deviation test, μ unknown, 233
 use in constructing five-point OC curve, 427
- Hall, Philip, 218n., 222
- Hartley, H. O., 386n., 394
- Hastay, Millard W., iii, ix
- Hayashi, Keiichi, 402n., 416
- Histogram, representation of population to which grouped data correspond, 193-195
- Homogeneity of binomial distributions, experiments for testing, 249-265, 424, 425
 analysis of data from, sequential sampling, 424-425
 single sample, 249-258
 planning of, sequential, 424
 single sample, 258-265
 of means, 61-62, 385-386
 of proportions, 249-265, 424, 425
 of 2×2 table, 249-265
 of variance estimates, 385-389
 Bartlett's test for, 385, 386, 387, 388
 Cochran's test for, 386, 387, 388, 389
 significance levels of, tables of, 390, 391
- Homogeneous variance, advantages of, 397, 398
 tests for, 385-389
 transformation of data to achieve, general formula for, 408, 409
 examples, 410-413
- Hotelling, Harold, ix, xi, 112, 114n., 149n., 154n., 155n., 172n., 184, 365n., 368n., 371n., 372, 398
- Hotelling's T , definition of, 142, 154, 155
 distribution of, 154, 155
 asymptotic expansion for percentage points of, 155
 free from nuisance parameters, 115
 relation to χ^2 -distribution, 155
 to F -distribution, 155
 optimum properties of, 147
 as "score," combining results of two or more tests, 113-116
- Hsu, P. L., 147, 166n., 184
- Hypotheses, statistical tests of (*see* Statistical tests)
- Hypothesis, alternative, 419, 420
 null, 420
 under test, 419, 420
- I
- Ignition current, 341
- Immediate acceptance, criterion for, in variables inspection for fraction defective, 34, 37, 41, 67, 69, 70
- Impossible region, indicating a mistake, 36, 37
 figures showing, 38-40
- Inconsistent requirements in specifications, 50n.
- Independence of acceptance tests, 51
 tables for, 249-255
 (*See also* Double dichotomy; 2×2 tables)
 of \bar{x} and s in samples from a normal population, 200
 effect of grouping or rounding on, 187, 201
- Indifference quality, definition of, 20
 use in variables inspection for fraction defective, 21
- Indifference value, 282
- Inferences about population (*see* Estimation; Statistical tests)
- Information about lot, 7
- Inspection, acceptance (*see* Acceptance inspection)
 amount of (*see* Amount of inspection)
 cost of (*see* Cost; Amount of inspection)
 curtailed, 14, 238, 361
 destructive, 9, 321, 331, 341
 normal, 43, 44
 plan, considerations involved and steps in choosing, 45-49
 reduced, 41-45
 sampling, effectiveness of, 156-158
 (*See also* Operating-characteristic curves)
 objections of, 156-158
 risks involved, 228, 229
 (*See also* Consumer's risk; Producer's risk)
 value of, dependent on quality of submitted product, 42
 for several quality characteristics, 50-52, 113-116
 tightened, 41-45
 variability of, 235-244
 by variables (*see* Variables, inspection by)
- Interpolated value, accuracy of, 219, 220n., 221n.
 error of, 219
 precision or variance of, 219-221
- Interpolation, 218-221
 coefficients, Lagrangian, 108, 109, 219, 222
 Salzer's inverse, 109
 without differences, 219
 harmonic in k or n , 317, 388
 in \sqrt{n} , 275, 316, 388
 inverse, 109
 probability wise, 316n., 318
- Interpreting, analysis-of-variance experiments, 297, 310-314
 experiments for comparing two proportions, 249-258
 for comparing two standard deviations, 267-318
 for determining whether variability of new process or product exceeds standard, 267-278
 is less than standard, 278-280
 for determining whether one of two processes is more variable than another, 280-296
 experiments when severity of any one test cannot be controlled precisely, 331-338

Inverse hyperbolic tangent, 413 (*see* *z*-transformation)

Inverse-sine transformation, of proportions, to stabilize variance, 257-259, 261-264, 336, 395-416

adjustment of, 399, 401-407

references to, 399n., 405n., 407n.

table to facilitate, 406

Bartlett's adjustment of, 399, 401-407, 413, 414

Bartlett's form of, 398, 406, 401

bias of, 403, 404

bibliography for, 414-416

derivation of, 410, 411

effectiveness of, 401-408

figures showing, 400-402

tables showing, 403-405

forms of, Bartlett's, 398, 400, 401

Bliss', 398, 400

Fisher's original, 398, 399, 400

SRG's first version, 405, 406

Yates', 398, 400

Zubin's, 257, 258, 398, 405

history of, 398

nature of, 399-400

presentation of final results, 407

tables to facilitate application of (*see* Bibliography, 414-416)

use to determine confidence limits for binomial parameter, 336

to determine number of trials needed in experiments for comparing two proportions, 259, 260

formula for, 259

derivation of, 261-264

nomogram based on, 260

use to determine OC curve of experiment for comparing two proportions, 261, 262

use in sequential analysis, references to, 405n., 415

Irwin, J. O., 218n., 222

Isaacson, E., 416

J

J-shaped curves, 194, 222

Jennett, W. J., 8n., 49, 58n., 72n., 93, 99

quotation from paper by, with B. L. Welch, 49-50

Johnson, N. L., 8n., 22, 64, 72, 73, 74, 76, 77, 79, 86, 93

K

K: difference between upper limit (*U*) specified for a variable and its population mean (μ), in units of population standard deviation (σ), 9-13

K: minimum proofing pressure prescribed for gun barrels, 331

K: multiple of *s* used in setting tolerance limits, 97-100

formulas for, 101, 108

table of values for, 102-107

uses of, examples of, 100, 101

K α : normal deviate exceeded with probability α (producer's risk, or probability of an error of first kind), 17, 278n.

formula for, 263

relation (of *K α*) to percentage points of χ^2 -distribution, 258n.

use in acceptance inspection, for average performance, 61, 62

for dispersion of performance, 231, 232, 278n.

for fraction defective, by attributes, 259, 260n., 261-264

by variables, 17-21, 60-63, 81, 82

for fraction of sample ranges less than specified limit, 231, 232

for mean quality of lot, 61, 62

for standard deviation of quality in lot, 231, 232, 278n.

use in formula for critical level (*A*) and number of observations needed in general single-sample, one-parameter test, 61, 62

use in planning experiments for comparing two proportions, 258-264

for comparing two standard deviations or variances, 278n.

use in probability-wise interpolations in percentage-point tables, 316n.

use in variables inspection for fraction defective, 17-21, 60-63, 81, 82

(*See also* *K β*)

K β : normal deviate exceeded with probability β (consumer's risk, or probability of an error of second kind), 17, 278n., 380

formula for, 263, 264

use to determine number of observations needed when decisions will be based on signs of differences between sample means, 380

(*See also* *K α* , uses for; *K ρ*)

K ϵ : normal deviate exceeded with probability ϵ , 17, 380

formula for, 17, 18, 31, 260

relation to "probit," 343

tables of, references to, 10n., 18, 313n.

need for care in using, 10n.

use in asymptotic expansion for percentage points of *t*-distribution, 148

uses, other (*see* *K α* and *K β* ; *K ϵ* ; *K γ* ; *K ρ* ; *K τ*)

K ϵ : normal deviate exceeded with probability ϵ , 21

K γ : normal deviate exceeded with probability γ , 336

K ρ : normal deviate exceeded with probability ρ , 21

K τ : normal deviate exceeded with probability τ , 17

K τ : normal deviate exceeded with probability τ , 17

k: coefficient of *s* in variables inspection plan for fraction defective, 12-14, 16-26

adjustment of, when *N* is fixed, 19, 20

approximate evaluation by formula, 17-20

comparison with exact values, 64-66

exact evaluation, from indifference quality, 21

using non-central *t*-distribution 71-82

formulas for, 17-20

derivation of, 59, 60, 82-83

table of values, 22-25, 65

- k : coefficient of s in variables inspection plan for fraction defective, uses of, additional, 27*n*, 28*n*.
- k : number of items the range (R_k) of which is critical, 227, 228
- k : number of samples to which a given acceptance number (A_k) or rejection number (R_k) corresponds, 237
(See also Acceptance number; Rejection number)
- k_A : acceptance level for k in sequential variables inspection for fraction defective, 84, 85
- k_0 : observed difference between upper limit (U) and sample mean (\bar{x}) in units of s ; sample estimate of K , 43
use in sequential variables inspection for fraction defective, 84, 85
- k_R : rejection level for k in sequential variables inspection for fraction defective, 84, 85
- k' : \sqrt{n} times coefficient of s in acceptance criterion, used when items are eventually assembled in sets of n , 48
- Kelley, Truman Lee, 18, 93
- Kendall, Maurice G., 120*n*, 184, 196*n*, 199*n*, 222
- Kohn, Anne Frankenthaler, x
- Kurtosis, measures of (β_4, γ_4), 197, 198
- of distribution of error of an interpolated value, 221
- of sample mean when data are grouped or rounded, 197, 198
- L
- L : upper limit of a measured quality characteristic, above which an item is defective, 72
(See also U)
- L_p : probability that a lot of fraction defective p will be accepted by a given acceptance inspection plan if submitted, 15, 16, 28
- evaluation of, 28-33, 50-52, 76, 77, 80, 358, 361, 427
- use of, in determining confidence limits for p , 43-45, 336
- L_{ϕ} : probability of concluding that $\sigma_2^2 \leq \sigma_1^2$ when $\sigma_2^2 = \phi \sigma_1^2$, 282
- curves showing, for F -tests of variance estimates, 296, 297, 318*n*.
- evaluation of, for F -tests of variance estimates, 282-296, 316, 317
- L_p : probability of concluding that $\sigma_1^2 \leq \sigma_2^2$ when $\sigma_1^2 = \rho \sigma_2^2$, 278
- curves showing, for χ^2 -test of variance estimate, 274, 275, 318*n*.
- evaluation of, for sequential sampling (see L_{ϕ}) for single-sample χ^2 -test, exact procedure, 271-278, 279, 315
- large-sample formula for (see L_{ϕ})
- L_{σ} : probability of concluding that $\sigma_2 \leq \sigma_1$ when $\sigma_2 = \sigma$, 232
- curve showing, for sequential test, 234
- evaluation of, for sequential sampling, 233
- for single-sample χ^2 -test, exact procedure, 232
- large-sample formula for, 232
- L_T : probability of concluding that $P_T > P_S$ when true angular difference between P_S and P_S is T , 262
- curve showing, 262
- evaluation of, by formula, 262
- from nomogram, 263
- L_{θ} : probability of concluding from likelihood ratio sequential test that $\theta \leq \theta_0$, as a function of the true value of θ , 427, 428
- $L_{\mu, \sigma}$: probability that a lot of mean μ and standard deviation σ will be accepted by a given acceptance inspection plan if submitted, 16, 52
- Lagrangian interpolation coefficients, 108, 109, 219, 222
- λ : natural logarithm of ratio to two probabilities or probability densities, computed after each observation in sequential analysis, 83
- $\lambda(f, t_0, e)$: function of f , t_0 , and e used in calculation of $\delta(f, t_0, e)$ and $t(f, \delta, e)$ from tables of non-central t -distribution, 74, 75
- λ_1 : value of $\lambda(f, t_0, e)$ computed in determining $p_{1-\alpha}$, 82
- λ_2 : value of $\lambda(f, t_0, e)$ computed in determining p_{β} , 82
- Landau, E., 408*n*.
- Langdon, W. H., 195*n*, 196*n*, 222
- Large samples, formulas and procedures valid for, 17-21, 30-33, 43, 58-63, 81, 82, 101, 108, 109, 148, 149*n*, 155, 162-163, 169, 231, 232, 263, 264, 278*n*, 336, 377-381, 393, 399-401, 407, 408-413
- accuracy of, 64, 65, 401-407
- when data are grouped or rounded, 196-203
- Least squares, application of, when cost of each measurement depends upon its magnitude, 319-328
- when data are observations on cumulative distribution, 343, 344
- references to, 343*n*, 352
- Lethality of drugs, 341
- Level of significance, 270, 271, 281
- Levine, Harriet, x, 6, 109, 149*n*, 184
- Levine, Myra, x, xi, 236
- Likelihood ratio, as basis for sequential tests, 83, 419-421
- definition of, 420
- formula for logarithm of (λ), in sequential binomial test, 421
- in sequential double-dichotomy test, 424
- in sequential mean test, σ known, 423
- σ unknown, 84
- in sequential variables inspection for fraction defective, 84
- Limits, confidence (see Confidence limits)
- control (see Control limits)
- of normal variation (see Tolerance limits)
- tolerance (see Tolerance limits)
- Lindley, D. V., 281*n*.
- Linear regression, when cost of each measurement depends upon its magnitude, 319-328
- when data are observations on cumulative distribution, 343, 344
- references to, 343*n*, 352

Location, estimation of parameters of (*see* Estimation; Mean; Median)

Logarithmic scale, 321

Logarithmic transformation, 412-413
(*See also* z-transformation)

Logarithms, of factorials, 253
reference to tables of, 253n.

Lot, acceptability of, determined by average quality, 6, 27, 26, 61-63
by dispersion of quality, 6, 27n., 28n., 229, 269, 270, 278-280, 283
by fraction defective, 7, 6
by fraction of averages of samples of n that exceed specified limit, 46
by fraction of ranges R_k in samples of k that exceed specified limit, 226, 229
formulation of, in terms of σ , 229-231
by mean quality (μ), 27, 26, 61-63
by mean (μ) and standard deviation (σ) of quality, 11
by several quality characteristics, 50-52, 113, 114
by standard deviation of quality, 8, 27n., 28n., 229, 269, 270, 278-280, 283
by upper and lower limits on a single quality characteristic, 52-56, 63, 64
(*See also* Acceptable quality; Acceptable-quality level)

acceptance of, meaning of, 13-14
procedure for (*see* Acceptance inspection)

judgment of, from a sample or samples (*see* Acceptance criterion; Acceptance inspection)

quality of, choice of standards for, 46-49
specification of (*see* Lot, acceptability of)

rejection of, meaning of, 13, 14

submitted, probability of acceptance (*see* Operating-characteristic curve)

variation of, from item to item, 8

Lot tolerance percent defective (LTPD; p_0), definition of, 43, 229
difference between true and intended, in variables inspection for fraction defective, 21-26
causes of, 21, 22
discussion of, 21, 22, 25, 26
table showing, 22-25
selection of, considerations in, 45-49

Lowan, Arnold N., x
(*See also* Mathematical Tables Project)

LTPD (*see* Lot tolerance percent defective)

M

M : minimum value of a measured quality characteristic, below which an item is defective, 13

m : two-point estimate of μ based on probit data, 350
formula for, 350
variance of, 351
with optimum arrangement, 352

Marginal totals, held fixed in analysis of 2×2 table, 251

Martin, Celia S., x

Massachusetts Institute of Technology, ix

Mathematical Tables Project, x, 10n., 31n., 83n., 93, 103, 109, 209n., 210n., 222, 255n., 260n., 265

Mather, K., 414n.

Matrices, numerical inversion of, 172-173

Maximum of a function, 365
design of experiments for determining, 363-372
factorial, 366, 367, 369-372
when form of function is known, 371
sequential, 367-372
single sample, reference to, 365n., 372
use of preliminary sample in, 371

Mean, arithmetic (*see* Arithmetic mean, Sample mean)

of binomial distribution, 397, 410
of grouped distribution, 193, 194
of lot (μ), as measure of lot quality, 6, 27, 28, 61-63
of normal distribution, 9, 12, 61, 97, 161, 197, 198, 342, 376, 423
variance of maximum likelihood estimator of, when data are grouped, 197
of Poisson distribution, 411
of population (μ), bias of sample mean as estimator of, when data are grouped or rounded, 167, 168, 212, 213
confidence limits for, σ known, 197, 198
 σ unknown, 99, 200-203, 213-215
decisions regarding, based on sign of difference between sample means, 377-382
estimation of, by sample mean, 162, 167, 168, 192, 196-198, 203, 212, 213
from observations on cumulative distribution, 342-352
optimum design of experiments for, 345, 346, 349-356
importance of distinguishing from sample mean (\bar{x}), 12
as parameter, 12, 161
tests of significance regarding, sequential, σ known, 423
 σ unknown, 83-85, 426
single sample, σ known, 61, 62
when data are grouped or rounded, 197, 198, 212, 213
 σ unknown, 61-63, 71-73
when data are grouped or rounded, 200-203
variance of maximum likelihood estimator of, when data are grouped or rounded, 197
of r , 413
of s , 56
of s^2 , 192, 412
when data are grouped or rounded, 199, 212, 213
of sample, as estimator of population mean, 12, 162, 167, 168, 192, 190-196, 203, 212, 213
bias of, when data are grouped or rounded, 167, 168, 203, 212, 213
(*See also* Expected value)

Mean deviation (mean absolute deviation), definition of, 162
as estimator of σ , 162, 163, 169

Mean error (*see* Mean deviation)

- Normal distribution, basis for "probits," 343
 bias of mean deviation as estimator of standard deviation of, 169n.
 bias of s as estimator of standard deviation of, 58, 162
 adjustment factor, formula for, 58
 tables of, references to, 58n.
 bias of s^2 as estimator of variance of, when data are grouped or rounded, 199
 in biological assay, 342
 bivariate, 146
 correlation coefficient of, 413
 relation of T to exponent of, 114-115
 characteristics of, 9-13, 97, 98, 161-163, 198, 199, 200, 202, 221, 229, 312, 378, 379, 381
 cumulative, estimating μ and σ from data on, 339-352
 optimum design of experiments for, 345, 346, 349-352
 departures from, seriousness of, in statistical analyses, 49, 50, 99, 198, 199, 202, 346, 377, 381
 dependences of proportion exceeding given limit on the parameters of, 10
 (See also Normal deviates)
 in dosage-mortality studies, 342
 of errors of tabular values, advantages that would accrue from, 221
 estimation of the parameters of, 12, 58, 161-163, 169
 from grouped or rounded data, 187, 188, 196-203, 212-214
 from observations on cumulative distribution, 339-352
 expected value, of mean deviation in large samples from, 169
 of s in samples from, formula for, 58
 of $\bar{x} + ks$ in samples from, 58
 figure, schematic, 10
 formula for, 161, 423
 for partial integral of, 17, 18, 31, 260, 263
 generalized, 197
 (See also Gram-Charlier series)
 grouped, distribution of s^2 in samples from, 198-200, 203-214
 of t in samples from, 200-203, 214, 215
 of \bar{x} in samples from, 196-198, 203, 212, 213
 independence of \bar{x} and s^2 in samples from, 200
 effect of grouping on, 187, 188, 201
 kurtosis, measured by β_2 or γ_2 , 197, 198
 of distribution of means from, when data are grouped or rounded, 197, 198
 mean of (μ), 9-12, 61, 97, 161, 162, 197, 198, 342, 378, 423
 estimation of, from observations on cumulative distribution, 342-352
 from probit data, 342-352
 by sample mean, 162, 187, 188, 192, 196-198, 203, 212, 213
 by sample median, 162
 tests of significance regarding, sequential, σ known, 423
 σ unknown, 83-85, 426
- Normal distribution, mean of (μ), test of significance regarding, single-sample, σ known, 61, 62, 197, 198, 212, 213
 σ unknown, 61-63, 71-73, 200-203
 variance of maximum likelihood estimator of, when data are grouped or rounded, 197
 parameters of, estimation of (see Normal distribution, estimation of parameters of; mean of; standard deviation of; variance of)
 notation for, emphasizing distinction from sample estimates, 12
 tests of (see Normal distribution, tests of significance regarding parameters of, mean of; standard deviation of; variance of)
 range in samples of k , cumulative distribution, figure showing, 230
 tables of, references to, 229, 230, 234
 distribution of, 234
 depends only on k and σ , 229
 as estimator of σ , 227
 mean values of, 227n., 234
 standard deviation of, 227n., 234
 standard deviation of (σ), 9-12, 97, 161, 229, 342, 426
 estimation of, from mean deviation, 162, 163, 169
 from observations on cumulative distribution, 342-352
 from probit data, 342-352
 from range, 227
 from s , 12, 58
 (See also Normal distribution, variance of)
 tests of significance regarding, sequential, 232, 233, 426
 single-sample, 200, 231, 270, 271, 274, 275, 278-280
 standard deviation of s in samples from, 58
 of $\bar{x} + ks$ in samples from, 58
 tables of, 18, 31
 need for care in using, 10n.
 references to, 10n., 18, 31, 148n., 149n., 343n.
 types of, 10n.
 tests of significance regarding parameters of, sequential, 83-85, 232, 233, 423, 426
 single-sample, 61-63, 71-73, 197, 198, 200-203, 212, 213, 231, 270, 271, 274, 275, 278-280
 (See also Normal distribution, mean of; standard deviation of; variance of)
 variance of, 161, 198, 199, 200, 212-214
 definition of, 161
 estimation of, by mean deviation, 162, 163, 169
 by s , 162, 198-200, 203-214
 tests of significance regarding, sequential, 232, 233, 426
 single sample, 200, 231, 270, 271, 274, 275, 278-280, 282, 283, 296
 (See also Normal distribution, standard deviation of)
- Normal inspection, 43-45
 acceptable-quality level for, choice of, 45-49

Normal law (*see* Normal distribution)
 Normal-probability function, tables of, 10a., 18, 31, 148n.-149n., 343n.
 need for care in using, 10n.
 types of, 10n.
 Normal-probability paper, 414
 Normal surface (*see* Normal distribution, bivariate)
 Normality assumption, avoided by use of attributes inspection, 8, 229n.
 by use of distribution-free tolerance limits, 90, 100
 dependence upon, of analysis of probit data, 346
 of moments of t -distribution, 201
 of OC curve for variables inspection plan for fraction defective, 49, 50
 of tolerance-limit factor K , 99
 of $\bar{x}_1 - \bar{x}_2$ as best decision function regarding sign of $\mu_1 - \mu_2$, 381
 importance of, in air testing of bombsights, 146
 in analysis of sensitivity data, 346
 in evaluating probability that sample means will be in opposite order to population means, 377, 378
 in setting tolerance limits, 99
 in variables inspection for fraction defective, 49, 50
 use of, when severity of any one test cannot be controlled precisely, 336
 Normally distributed test function, derivation of critical level (A) and number of observations needed (N) for, 61, 62
 Notation, as means of emphasizing distinction between parameters of population and sample estimates of these, 12
 used in variables inspection for fraction defective, 85-96
 Nuisance parameters, 115
 Null hypothesis, 420
 in analysis of variance, 311, 312
 in mean tests, 386, 423
 in proportion tests, 249, 251, 264, 357, 358, 421, 424
 in standard deviation or variance tests, 270, 278, 281, 386, 387, 311, 312

O

OC (*see* Operating Characteristics)
 OC curves (*see* Operating-characteristic curves)
 OC surface (*see* Operating-characteristic surface)
 Office of Scientific Research and Development (OSRD), vii
 (*See also* National Defense Research Committee)
 Omnibus tests, 386
 Old method, process, or product compared with new, with respect to fraction defective, 249-264, 424, 425
 with respect to level of performance, 59-63, 380
 with respect to variability of performance, 280, 282, 283, 296
 (*See also* Standard)

One-decision sequential binomial test, 358
 One-sided criteria, use of a pair of, in variables inspection for fraction defective, 53, 54
 compared to use of a single two-sided criterion, 52, 56
 figure showing acceptance and rejection regions in (\bar{x}, s) -plane, 55
 One-sided or one-tail tests, of statistical hypotheses, 52-57, 150, 152, 156, 426
 Operating characteristics (OC), 15, 16, 28-32, 261-263, 271, 278
 definition of, 14, 281, 271
 Operating-characteristic curves (OC curves), 15, 29, 234, 263, 274, 275, 296, 297, 379
 for analysis-of-variance tests, 313, 314
 for attributes inspection, sequential sampling, 426, 427
 single sample, 260n., 262, 263
 when averages in samples of n determine lot quality, 48
 for binomial test, one-decision (R_p), sequential, 358
 one-sided, sequential, 426, 427
 single sample, 260n., 262, 263
 truncated, sequential, 361
 for χ^2 -test of variance estimate (L_p, L_e), 231, 232, 271-279, 316, 318n.
 figures showing, 274, 275, 315n.
 large-sample formula for, 232
 tables for constructing, 272, 273, 276, 277
 when decisions are based on signs of differences between sample means [$P(\delta, N)$], 378-380
 figure showing, 379
 table for constructing, 378
 definition, 15, 16, 28, 41, 42, 232, 278, 358, 427
 detailed, for single-sample variables inspection plan for fraction defective, determining, 30-33
 determines what fraction of production submitted will be accepted, 47
 as determining factor in cost of quality, 46
 for difference of means test, σ known, 61, 62
 σ unknown, 30, 59-61, 62, 63, 71-73, 76, 77, 80
 for difference of proportions test, sequential, 424, 426, 427
 single sample (L_r), 262, 263
 figure showing, 262
 for double-dichotomy test, sequential, 424, 426, 427
 single-sample (L_r), 262, 263
 figure showing, 262
 for double-sampling plans, reference to, 238
 effects of changes in acceptance criterion on, 21, 45
 of changes in sample size, 21, 45
 of reduced inspection, 45
 of simultaneous use of several acceptance-rejection criteria, 50-52, 113, 114
 of tightened inspection, 45
 for experiments for determining whether fraction defective of one process or product exceeds another, sequential, 424, 426, 427

- Operating-characteristic curves (OC curves), for experiments for determining whether fraction defective of one process or product exceeds another, single-sample (L_r), 262, 263
- figure showing, 262
 - whether level of performance of one process or product exceeds another, 30, 59-63, 71-73, 76, 77, 80
 - whether variability of performance of one process or product exceeds another (L_ϕ), 281-283, 296, 316, 317, 318n.
 - figures showing, 296, 297, 318n.
 - tables for constructing, 284-295, 298-309
 - whether variability of performance of one process or product exceeds standard (L_p, L_σ), sequential, 233
 - single sample, 231, 232, 271-278, 315, 318n.
 - figures showing, 234, 274, 275, 315n.
 - large-sample formula for, 232
 - tables for constructing, 272, 273, 276, 277
 - whether variability of performance of one process or product is less than standard, 279
 - for F -tests of variance estimates (L_ϕ), 281, 283, 296, 313, 314, 316, 317, 318n.
 - figures showing, 296, 297, 318n.
 - tables for constructing, 284-298, 298-309
 - figures showing, 15, 29, 234, 263, 274, 275, 296, 297, 379
 - references to, 238n., 318n.
 - five-point, 28-30, 427
 - figure showing, 29
 - for fraction defective tests (see Operating-characteristics curves, attributes inspection; variables inspection)
 - for general one-parameter tests, sequential (L_ϕ), 426-427
 - single sample, 61, 62
 - information provided by, 15, 16, 28, 41, 42, 278, 358, 427
 - interpretation of, 15, 16, 28, 41, 42, 232, 278, 358-427
 - location of, 21, 45
 - for mean test, single sample, σ known, 61, 82
 - σ unknown, 30, 59-63, 71-73, 76, 77, 80
 - of multiple-sampling plans, references to, 238
 - steps in computation of, outlined, 361
 - for one-decision sequential binomial test (R_p), formula for, 358
 - ordinate of, 15, 16, 28, 41, 42, 232, 278, 358, 427
 - for proportion test, sequential sampling, 426, 427
 - single sample, 260n., 262, 263
 - when range in samples of k determines lot quality (L_p, L_σ), sequential sampling, 233
 - figure showing, 234
 - single sample, 231, 232, 271-278, 279, 315, 318n.
 - figures showing, 274, 275, 315n.
 - for sequential-sampling plans, 233, 358, 361, 426, 427
- Operating-characteristic curves (OC curves), for sequential-sampling plans, general procedure for constructing one-parameter tests (L_ϕ), 426, 427
- five-point, 427
 - for one-decision tests (R_p), 358
 - for specific tests (see the test concerned)
 - for truncated tests, outline of steps for computing, 361
 - when several acceptance-rejection criteria are used simultaneously, 50-52, 113, 114
 - for single-sample inspection plans and tests' (see the test concerned)
 - as specification of what will be accepted, 46
 - for standard deviation tests (L_ϕ, L_p, L_σ), sequential, 233
 - figure showing, 234
 - single sample, 231, 232, 271-278, 279, 281-283, 296, 315-317, 318n.
 - figures showing, 274, 275, 296, 297, 315n.
 - large-sample formula for, 232
 - tables for constructing, 272, 273, 276, 277, 284-296, 298-309
 - steepness of, 21, 45
 - typical, figure showing, 15
 - when upper and lower limits are imposed on a single quality characteristic, 52
 - use of, to determine what fraction of production submitted will be accepted, 47
 - use in selecting plan of action, 15
 - for variables inspection plans for fraction defective, 15, 16, 21, 28-33, 41, 42, 45-50, 52, 65, 66, 71-73, 76, 77, 80
 - when averages in samples of n determine lot quality, 48
 - computation of, from large-sample formula, 30-33
 - from non-central t distribution, 71-73, 76, 77, 80
 - dependence on normality assumption, 49, 50
 - effect of changes in N or k on, 21, 45
 - figure showing, 29
 - large-sample formula for, 30
 - plotted as function of $K = (U - \mu)/\sigma$, 49
- Operating-characteristic surface, 16, 52, 261, 262
- Order of sample means, number of observations needed when decisions are based on, 380, 381
- optimum decision function, 381, 382
- probability opposite to population means, 377-380
- figure showing, 379
 - formula for, 379
 - table giving, 378
- Ordered magnitudes, 367, 368n.
- Ore, Oystein, 195n., 196n., 222
- Origin, shifting, to simplify graphical procedure for variables inspection, 56, 37, 41, 54, 69-71
- P
- P : parameter of binomial distribution, 250, 251
- P : proportion of items with given attribute in infinite population, 255, 256, 397, 410

- P : proportion of population or lot to be included between tolerance limits, 47n., 93, 99
- P : true long-run probability of "success" in any single trial, 250, 251
(See also p)
- P_E : value of P for experimental or new method, process, or product, 259
- P_S : value of P for standard or old method, process, or product, 259
- P_0 : probability or probability density corresponding to observations in hand, if null hypothesis is true, 420
as denominator of likelihood ratio, 420
use of logarithm of, to simplify sequential analysis, 421
- P_1 : probability or probability density corresponding to observations in hand, if alternative hypothesis is true, 420
as numerator of likelihood ratio, 420
use of logarithm of, to simplify sequential analysis, 421
- $P(\delta, N)$: probability sample mean based on N observations will be in opposite order to population means when latter differ by δ standard deviation units, 378, 379
figure showing, 378
table of, 379
- PA: process average percent defective, 42
- p : fraction defective in lot, 15
- p : observed proportion, 255, 397, 410
- p : parameter of binomial distribution, 421
- p : true long-run proportion of "successes" with a given method, 421
- $p_1 - \alpha$: the fraction defective for which the probability of acceptance is $1 - \alpha$ with a given sampling plan, 82
- p_β : the fraction defective for which the probability of acceptance is β with a given sampling plan, 82
- p_E : observed proportion of successes with experimental method, 256
- p_S : observed proportion of successes with standard method, 256
- p : indifference quality, 20, 29
- p_0 : value of p when null hypothesis is true, 421
- p_1 : acceptable-quality level, 16, 229, 357, 359
(See also Acceptable-quality level)
- p_1 : value of p for first of two methods, processes or products, 421
- p_2 : value of p when hypothesis alternative to $p = p_0$ is true, 421
- p : lot tolerance percent defective, 16, 229, 357, 359
(See also Lot tolerance percent defective)
- p_2 : value of p for second of two methods, 424
- p' : fraction defective for which probability of acceptance (L_p') is $1 - L_p$, 32
- Pairman, Eleanor, 164n., 222
- Parameter, of binomial distribution (P, p), 250, 251, 421
of Poisson distribution, 411, 426
of population, distinguished from statistic and sample estimate, 12, 161
- Park, R. H., 335n.
- Paulson, Edward, ix, xi, 99, 109, 248, 393, 394, 418n.
- Peach, Paul, 48n., 93
- Pearse, G. E., 194n., 223
- Pearson, Egon Sharpe, 166n., 184, 229, 230, 234, 271n., 318, 335n., 386n., 389n., 393, 394
quotation from article by, on "omnibus" tests, 386
quotation from letter of, on accuracy of confidence belt charts, 335
- Pearson, Karl, 194n., 222, 223
- Pegram, George B., x
- Peiser, A. M., 149n., 184
- Percent defective (see Fraction defective)
- Percentage points of statistical test functions (see Significance levels)
- Percentages (see Proportions)
- ϕ : transformed proportion, 398, 399
(See also Inverse-sine transformation)
- ϕ_S : transformed proportion with Bartlett's adjustment, 401
(See also Bartlett's adjustment; Inverse-sine transformation)
- ϕ : the ratio of two variances (σ_1^2/σ_2^2), 281
- $\phi(\alpha, \beta, n_1, n_2)$, formula for, 282
derivation of, 281n., 316, 317
special cases of, 282
tables of, 284-295, 298-309
- π : ratio of circumference of a circle to its diameter, 189
value correct to 20 decimal places, 189n.
value expressed as common fraction, correct to 6 decimals, 189n.
- Pitman, E. J. G., 386n., 391
- Plan of action, of an acceptance inspection plan, definition of, 13
for locating maximum of a function, sequential procedure for, 367-369
suitability of, shown by OC curve, 15
for variables inspection for fraction defective, outline of, 14
procedures for, 16-21, 33-41
- Planning experiments, 243-372 (see Design of experiments)
- Plans for experiments (see Experiment designs)
- Poisson distribution or series, relation of partial sum to percentage points of χ^2 , 109
mean, variance, third and fourth moments of, 411
sequential procedure for testing parameter of, 426
tables of, reference to, 109
transformation of, to stabilize variance, derivation of, 411, 412
(See also Square-root transformation)
- Population, or universe, 12, 98, 227, 251, 341, 355, 377
(See also Lot)
- Population mean (μ, \bar{x}), 12, 161
(See also Confidence limits, for μ ; Estimation, of population mean; Mean, of population; Statistical tests, relating to population mean)

- Population proportion (P, p), 255-256, 397, 410
 (See also Binomial distribution, parameter of;
 Confidence belts; Confidence intervals;
 Confidence limits; Estimation; Proportion,
 population; Statistical tests)
- Population standard deviation (σ), 12, 161
 (See also Confidence limits; Estimation;
 Standard deviation, of population; Statis-
 tical tests)
- Population variance (σ^2), 12, 181
 (See also Confidence limits; Estimation;
 Statistical tests; Variance, population)
- Power function, of a statistical test procedure, 427
 (See also Operating-characteristic curves,
 Operating-characteristic surface)
- Precision (see Standard deviation; Variance)
- Preliminary sample, use of, in attributes inspec-
 tion when severity of any one test cannot be
 controlled precisely, 336-338
 in planning regression studies, when cost of
 each measurement depends upon its
 magnitude, 321-328
 in planning sensitivity tests, 345, 346, 349-
 352
- Preliminary trial of an examination, evaluating,
 280
- Princeton University, ix
- Probabilities, compounding, 107
- Probability, absolute, 251
 of acceptance, 15, 18, 28-33, 41, 42, 45, 50-52,
 232, 233, 201-283, 271, 278, 279, 282, 315-
 317, 358, 361, 427, 428
 (See also Operating characteristics; Operat-
 ing-characteristic curves; Operating-
 characteristic surface)
 effect upon, of changes in acceptance cri-
 terion, 21, 45
 of changes in sample size, 21, 45
 of reduced inspection, 45
 of simultaneous use of several acceptance
 criteria, 50-52, 113, 114
 of tightened inspection, 45
 evaluation of (see L_p ; L_d ; L_p ; L_d ; L_r ; $P(3, N)$;
 Computation, of OC curve)
 conditional, 251
 density or density function, 83, 155, 161, 193-
 195, 217, 270, 281, 342, 392
 definition of, 193n.
 distributions, 10, 61, 62, 72, 73, 90, 109, 114,
 154, 155, 193-195, 197-199, 202, 214, 215,
 229, 230, 251, 270, 281, 342, 392
 element of, 155, 161
 (See also Probability, density)
 function of (see Probability, distributions)
 that gun barrel will be proofed, 332
 paper, arithmetic normal, 414
 binomial, 414n.
 that proximity fuze will operate, 342
 that sample means will be in opposite order to
 population means, 378-380
- Probability-wise interpolation, 316n., 318
- Probits, analysis of data expressed as, 342-344
 definition of, 343
 estimation of μ and σ from, 343, 350
- Probits, experiments leading to data expressed
 as, 341, 342
 optimum design of, 345-346, 349-352
 relation to normal deviates, 343
 tables of, references to, 343n., 352
 variance of, formula for, 350
- Process, average (see Process average percent
 defective)
 new (see New method)
 old (see Old method)
 quality level of (see Process average percent
 defective)
 standard (see Standard method)
- Process average percent defective (P'A), 42-45
 computation of confidence interval for, from
 attributes data, 333-336
 from variables data, 42-45
 as criterion for determining whether to main-
 tain or change volume of inspection, 42
 example of, 44
 estimation of, from attributes data, 333-336
 from variables data, 42-45
- Process control, contrasted with acceptance
 inspection, 156, 157
 importance of \bar{x} and s in, 31
 (See also Quality control)
- Producer's risk (α), conventional value of (5%),
 45n.
 definition of, 16, 228, 229
 maximum of, with variables inspection plans
 for fraction defective, 16, 17
 selection of, factors to consider in, 45-49
- Product, new (see New method)
 old (see Old method)
- Product-moment coefficient of correlation, 413
- Production possibilities, analysis of, 46, 47
- Proof testing, statistical aspects of, 331-338
- Proofing gun barrels, 331-338
- Proportions or percentages, 15, 47n., 98, 99, 250,
 251, 255, 256, 259, 397, 410, 421, 424
 ASN curve for sequential one-sided test of,
 figures showing, 240, 242
 formula for, 427, 428
 confidence limits for (see Proportions, popula-
 tion)
 estimation of (see Proportions, population)
 expected value of, 397, 410
 experiments for comparing two, analysis of
 data from, 249-258, 424, 425
 approximate single-sample method, based
 on binomial test, 249, 250, 255
 based on x , 253-255, 246-257
 based on inverse-sine transformation,
 257, 258, 263, 264
 based on normal deviates, 253-257, 263
 "exact" single-sample method, 250-253
 by Fulcher-Zubin Item Analyzer, 257,
 257n., 258
 incorrect method for, 256
 nomograph for, Zubin's, references to, 398,
 416
 by sequential analysis, 424, 425
 design of, 258-265, 424, 426-428

Proportions or percentages, experiments for comparing two, inverse-sine transformation of data from, 257, 258, 263, 264, 397-408
 number of observations needed, with sequential sampling, 424, 427, 428
 with single samples, 258-261, 264
 formula for, 258, 259, 264
 nomogram for, 260
 operating characteristics of, 261
 operating-characteristic curve (OC curve) of, determination, by formula, 262
 from nomogram, 263
 figure showing, 262
 operating-characteristic surface (OC surface) of, 261, 262
 planning of, 258-265, 424
 sequential, 424, 425, 426-428
 experiments for estimating population or true (see Proportions, population)
 experiments for testing a single, analysis of data from, 260n., 263, 264, 421, 422
 ASN curves for double, multiple, and sequential sampling of, 240, 242
 design of, 259, 260n., 261-264, 424, 426-428
 inverse-sine transformation of data from, 397-408
 number of observations needed, with double sampling, 237-244
 figures showing, 240-243
 with multiple sampling, 237-244
 * figures showing, 240-243
 with sequential sampling, 26, 237-244, 419, 420, 427, 428
 figures showing, 240-243
 formula for, 427, 428
 with single sampling, 14, 15, 26-28, 250, 260n., 263, 264
 examples, 26
 formula for, 259, 260n., 263, 264
 nomogram for, use of, 260n.
 OC curve of, approximate determination from formula, 260n., 262
 from nomogram, 260n., 263
 exact determination of points on, using confidence-belt charts, 336n.
 using percentage points of incomplete beta function, 334, 336n.
 planning of, 259, 260n., 261-264, 426-428
 sequential, 421, 422, 427, 428
 one-decision test, 353
 moments of, 410
 population, 15, 47n., 98, 99, 250, 251, 421
 bias of estimation from $\varphi(p)$ and $\varphi_n(p)$, 403, 404
 tables showing, 400-402
 estimation of, confidence belts for, 332-335
 confidence intervals for, based on attributes inspection, 332-336
 based on variables inspection, 42-45, 336n.
 confidence limits for, evaluation from percentage points of incomplete beta function, 333, 334, 337
 formula for, 335, 336

Proportions or percentages, population, estimation of, experiments for, analysis of data from, 332-336
 experiments for, design of, 238, 333-337
 inverse-sine transformation of data from, 336
 number of observations needed, 333-337
 sequential, 238n.
 included between statistical tolerance limits, 47n., 98-99
 standard deviation of, 255, 397, 410
 tests of significance regarding (see Proportions, experiments for...)
 transformation of, to stabilize variance, 257, 258, 263, 264, 397-408
 (see Inverse-sine transformation)
 variance of, 397, 410
 Protection afforded by sampling inspection, 46, 47, 156-158
 Przyborowski, J., 46n., 93, 255n., 265
 Psychological considerations, 278

Q

Quality, acceptable, 61, 228, 229, 269, 278, 279, 423
 (See also Acceptable-quality level)
 of accepted lot or product, 16, 41, 42, 46, 156-158
 attainable, 46, 47
 bad (see Quality, unacceptable)
 choice of standards of, 45-49
 control of (see Quality control)
 (See also Control charts; Control limits)
 cost of, OC curve a determining factor in, 46-47
 desired, 45, 46
 evaluation of (see Quality, of lot; Quality, produced by process)
 feasible, 45-47
 good (see Quality, acceptable)
 high, 42, 43
 improvement of, 46
 information about, 42
 provided by process average percent defective, 43
 by sampling inspection, 156-158
 by statistical tolerance limits, 47, 97-100
 of an item, 7
 of lot, determined by average quality of items of lot, 8, 27-28, 61-63
 by dispersion of quality of items of lot, 8, 27, 28, 229, 269, 270, 278, 279, 280, 283
 by fraction defective, 7, 8
 combinations of μ and σ that correspond to same fraction defective, 11
 by fraction of averages of samples of n that exceed specified limit, 48
 by fraction of ranges R_k in samples of k that exceed specified limit, 228, 229
 formulation in terms of σ , 229-231
 by mean quality (μ) in conjunction with dispersion of quality (σ), 11
 by mean quality (μ) of items of lot, 8, 27, 28, 61-63

- Quality**, of lot, determined by several quality characteristics, 50-52, 113, 114
 by standard deviation (σ) of qualities of items of lot, 8, 27n., 28n., 229, 269, 270, 278, 279, 280, 283
 by upper and lower limits on a single quality characteristic, 52-56, 63, 64
 by variability of quality among items of lot, 8, 27, 28, 229, 269, 270, 278-280, 283
 evaluation of (*see* Confidence intervals; Confidence limits; Estimation; Tolerance limits)
 judgment of, from a sample or samples (*see* Acceptance criterion; Acceptance inspection)
 submitted, 16, 41, 42, 46, 156-158
 low, 42, 43
 maintenance of, 43n.
 measures of (*see* Quality, of lot)
 of outgoing product, 16, 41, 42, 46, 150-158
 poor, 42, 43
 produced by process, evaluation of (*see* Confidence intervals; Confidence limits; Estimation; Process average percent defective; Tolerance limits)
 information about, provided by process
 average percent defective, 43
 by sampling inspection, 156-158
 by statistical tolerance limits, 47, 97-100
 of a sample, determined by sample average, 48
 by sample range, 228, 229
 submitted, 16, 41, 42, 46, 156-158
 unacceptable, 45n., 47-49, 229
Quality control, applied to air testing of bomb-sights, 113-184
 contrasted with acceptance inspection, 117, 156-158
 feature, in procedure for going on reduced inspection, 43n.
 functions of, 117
 importance of \bar{x} and s in, 34
 multivariate, 113-184
 use of a single "score" or "index" in, 113, 114
 based on generalized Student T , 114-116
 advantages of, 115
 objectives of, 156, 157
 (*See also* Control charts; Control limits)
- R**
- R_k**: acceptance number for the k^{th} sample, 237
 (*See also* Rejection number)
R_k: range of a sample of k items, 229
 (*See also* Range)
r: observed product-moment coefficient of correlation, 413
 z-transformation of, to stabilize variance, derivation, 413
Radio proximity fuse, 341
 analysis of test data, method of, 342-344
 design of tests of, optimum, 345-352
Random selection, of bomb-sights, reasons for, 158
Random variation, components of, 269, 297, 310
 311
 estimation of, and tests of hypotheses regarding, 311-314
Randomization, methods of, 176, 177
 as precautionary measure, 118
 to prevent bias from time trends, 371
 restricted, 177
 role of, in design of experiments, 141, 142, 176, 177
Range, calculation of, 227
 definition of, 227
 distribution of, in samples from a normal population, 234
 cumulative, 229
 figure showing, 230
 tables of, reference to, 229, 234
 mean of, table, reference to, 227n.
 standard deviation of, 227n.
 as estimator of σ , 227
 efficiency of, in small samples from a normal population, 227n.
 as measure of dispersion of sample, 227
 reasons for use, 227
 in samples of k , primary characterization of lot quality, 227, 228
 acceptance inspection when, 227-234
Range of normal variation, 97
 (*See also* Tolerance limits)
Rational centencing of lots, 156, 157
Rectangular distribution, 195, 217, 218
 as representation of grouping or rounding errors, 195
 for tabular entries, 215-218
 semi-invariants of, 195, 196n.
 standard deviation of, 218
 use of, in checking sums and tables, example, 218
 variance of, 195, 218
Reduced inspection, 41-45
 criterion for changing to, when lot quality is measured by fraction defective, 42
 procedure for judging whether criterion is met, using variables data, 42-45
 when upper and lower limits are imposed on a single quality characteristic, 56
 effect of, on OC curve, 45
 methods of achieving, with variables inspection for fraction defective, 45
 purpose of, 41, 42
Redundant requirements in specifications, 50n.
Rees, Mina, x
Regression analysis, when cost of each measurement depends upon its magnitude, 319-328
 when dependent variable is expressed in probits, 342-344, 349-352
Rejection criterion, for sequential likelihood ratio tests, 420, 421
 for sequential variables inspection for fraction defective, 83, 85
 for single-sample tests (*see* Acceptance criterion)
 (*See also* Rejection line; Rejection number)
Rejection line, 232, 357-360, 422, 423, 425
 adjusting, to allow for acceptance line, 358-360

- Rejection line, figure showing, 357
 for number of "successes" in binomial test, 422
 for number of "success-failure" pairs, in double-dichotomy test, 425
 for one-decision binomial test, 358
 for sum of observations, in test for μ , σ known, 423
 for sum of squared observations, in test for σ , μ unknown, 232
- Rejection number (R_k , S_i), 237, 239, 244, 358, 422, 425
 definition of (R_k), 237
 in double sampling, 237
 examples, 239, 244
 in multiple sampling, 237
 examples, 239, 244
 relation to acceptance number (A_k) characterizes type of sampling plan, 237
 in sequential sampling (R_k), 237
 in sequential tests (S_i), 422, 425
 in sequential tests that provide for rejection only, 358
 in single sampling, 237, 260n., 263, 264
- Rejection region, boundaries of, for sequential tests (see Rejection line)
 for single-sample tests (see Acceptance region, boundaries of)
- Relationship, determining, when cost of each measurement depends upon its magnitude, 319-328
- Replication, dual role of, in experimentation, 159
- ρ : product-moment coefficient of correlation in normal bivariate population, 413
- ρ : ratio of population variances (σ_1^2/σ_2^2), 271
- $\rho(\alpha, \beta, n_1)$, definition of, 271
 large-sample formula for, 278n.
 tables of, 272, 273, 276, 277
 use of, examples of, 271, 274, 275, 278
- $\rho'(\alpha, \beta, n_1)$, definition of, 279
 relation to $\rho(\alpha, \beta, n_1)$, 279
 use of, example of, 280
- Ridger, Paul R., 386n., 394
- Rietz, Henry Lewis, 196n., 197n., 218n., 223
- Risks, in use of sampling inspection, 150, 157
 (See also Consumer's risk; Operating-characteristic curves; Producer's risk)
- Robbins, Herbert, 109
- Rodermund, Edythe B., x
- Romig, Harry G., 27n., 93
- Rounded numbers, impossibility of avoiding use of, 188, 189
 measurements as, 187-189
 scale readings as, 188, 189
 tabular entries as, 191, 215-218, 221
- Rounding, 187-223
 accepted procedure for, 189, 190
 (See also Rounding Rule)
 Cayley's procedure for, 191
 effect of, on descriptive statistics, 187, 188
 on distribution of error of an interpolated value, 221
 of F , 214, 215
 of s^2 , 198-200, 203-214
 of Student's t , 200-203, 214, 215
 of \bar{x} , 196, 198, 212, 213
- Rounding, effect of, on moments of probability distributions, 193-196
 representation as effect of random "errors," 195
 on standard procedures for statistical inference, 191-215
 impossibility of avoiding, 188, 189
 reasons for, 187-189
 repeated, consequences of, 190, 191
 (See also Rounding interval; Rounding lattice; Rounding rule; Sheppard's corrections)
- Rounding interval, recommended size of, 192, 214
 reasons for, 214
- Rounding lattice, effect of position of, on distribution of s^2 , 206-213
 on distribution of \bar{x} , 212, 213
 random location of, 194
 extends validity of Sheppard's corrections, 195
 procedure for, when only non-negative values occur in population, 190
- Rounding rule, 189, 190
 Cayley's form of, 191
 effect of repeated applications of, 190, 191
 elementary properties of, 190, 191
 importance of adhering to, 190
- Roy, S. N., 184
- Royalties, vii
- S
- S : sensitivity of a fuse, 342
- s : sample estimate of population standard deviation (σ), based on sum of squared deviations from sample mean, 12, 13, 162, 192
 adjustment of, 58
 advantages of, relative to mean deviation, 162, 163
 relative to sample range, 227n.
- association of values of, with values of \bar{x} , when data are grouped or rounded, 187, 188
- bias of, 58
 adjustment factor, formulas for, 58
 tables of, references to, 58n.
 when computed from grouped or rounded data (see s^2)
- combining values of, to estimate variability of process, 42-43
- computation of, 12, 13, 33, 34, 42, 43, 162, 192
 $N - 1$ versus N in, 13, 68
 naive procedure for, criticism of, 33
 using modern computing machines, 33, 34
- definition of, 12, 13, 162, 192
 $N - 1$ versus N in, 13, 58
- degrees of freedom of, 12, 13, 43
 (See also s^2 , degrees of freedom of)
- division by, in computing, 12, 13, 43
- as denominator of Student's t , 72, 200
 Sheppard's corrections not to be used for, 203
- design of experiments for testing, 269-290
- distribution of, approximately normal for large N , 58

- s : sample estimate of population standard deviation (σ), distribution of, mean of, formula for, 58
 - tables of, references to, 58n.
 - standard deviation of, formula for, 58
 - tables of, references to, 58n.
 - (See also s^2 , distribution of)
 - effect of grouping or rounding of data on (see s^2)
 - efficiency of, 162, 227
 - expected value of, in normal samples, formula for, 58
 - tables of, references to, 58n.
 - formula for, 12, 13, 43, 162, 192
 - grouping of data, effect on, 187, 188 (See also s^2)
 - homogeneity of two or more values of, 383-389
 - importance of distinguishing from σ , 12
 - importance of, in quality control, 34, 42-44
 - largest of several values of, testing of, 383-394
 - logarithmic transformation of, to stabilize variance, 412, 413
 - mean of, in normal samples, formula for, 58
 - tables of, references to, 58n.
 - multiple of, for setting tolerance limits (see K)
 - used in variables inspection for fraction defective (see k)
- $N - 1$ versus N , in definition and computation of, 13, 58
- standard deviation of, in normal samples, formula for, 58
 - tables of, references to, 58n.
- termed "sample standard deviation" for brevity, 12, 13
- tests of significance regarding (see s^2)
- transformation of, to stabilize variance, 412, 413
- use of, in acceptance inspection for σ , 231, 232, 270, 271, 278-280
 - in acceptance inspection when ranges in samples of k determine lot quality, 227-234
 - in computing control limits for means, 147, 148
 - in estimating process average percent defective, 41-44
 - opposition to, rebuttal of, 33, 34
 - in quality control, 34, 42-44, 151, 152
 - in setting tolerance limits, 47
 - in variables inspection for fraction defective, 9-14, 33, 34, 41-44, 48, 53, 56, 58-64, 71-73, 83-85
- s : sample estimate of population standard deviation (σ), based on cumulative distribution (probit data), 343, 350
 - variance of, 351
 - with optimum experimental design, 352
- s : slope of parallel lines in graphical sequential analysis, 232, 233, 357, 358, 426, 427
 - formula for, binomial test, one-decision, 358
 - binomial test, one-sided, 422
 - double-dichotomy test, 425
 - mean test, σ known, 423
 - standard deviation test, μ unknown, 233
 - use in constructing ASN curve, 233
 - five-point, 427
- s : slope of parallel lines, in graphical sequential analysis, use in constructing OC curve, 233
 - five-point, 428
- sz : observed number of "successes" in N trials with experimental method, 262
- sz : observed number of "successes" in N trials with standard method, 262
- s^2 : sample estimate of population variance (σ^2), 12-13, 43, 162, 198
 - bias of, when computed from grouped or rounded data, 198-200, 203-214
 - computation of, 12, 13, 33, 34, 42, 43, 162, 198
 - control limits for, 151
 - correlation of, with \bar{z} , when computed from grouped or rounded data, 187, 201
 - definition of, 12, 13, 43, 162, 198
 - degrees of freedom of, 12, 13, 43, 199, 203, 270, 312, 387, 388
 - design of experiments for determining and testing, 269-268
 - distribution of, mean of, in sample from arbitrary grouped or rounded populations, 199
 - in large samples from arbitrary population, 199
 - effect of grouping or rounding on, 198-200
 - in samples from a normal population, 199, 270
 - effect of grouping or rounding on, in large samples, 198-200
 - in small samples, 203-214
 - variance of, in samples from arbitrary, grouped, and normal populations, 199
 - effect of grouping or rounding of data on, 187, 188, 198-200, 203-214
 - efficiency of, 162
 - expected value of, in samples from arbitrary, grouped, and normal populations, 199
 - formula for, 12, 13, 43, 162, 198
 - grouping of data, effect on, 187, 188, 198-200, 203-214
 - homogeneity of two or more values of, testing of, 385-389
 - importance of distinguishing from σ^2 , 12
 - independent of \bar{z} in samples from normal population, 200
 - effect of grouping or rounding on, 187, 188, 201
 - largest of several values of, testing, 383-394
 - logarithmic transformation of, to stabilize variance, 412, 413
 - mean of, in samples from arbitrary, grouped, and normal populations, 199
 - moments of, in samples from a normal population, 412
 - tests of significance regarding, sequential, 232, 233, 426
 - single sample, 231, 232, 269-266, 383-394
 - transformation of, to stabilize variance, 412, 413
 - uses of, special (see s)
 - variance of, in samples from arbitrary population, 199
 - when data are grouped or rounded, 199
 - in samples from normal population, 199

- s^2 : sample estimate of population variance (σ^2), variance of, in samples from normal population, when data are grouped or rounded, 211
yardsticks for, 152
Salzer, H. E., 109, 416
Sample average (*see* Sample mean)
as basis for decisions, 156-158
(*See also* Consumer's risk; Operating characteristics; Operating-characteristic curves; Producer's risk)
mean (*see* Sample mean)
median (*see* Median)
random, 158-160
representative, 160
selection of, 158-160
size of (*see* Sample size)
Sample mean (\bar{x}), 12, 43, 100, 192
advantages of, relative to sample median, in normal samples, 161, 162
bias of, when data are grouped or rounded, 187, 188, 197, 212
combining, from several samples, in estimating process average percent defective, 42, 43
computation of, 12, 43, 100, 192
control limits for, 147-150
correlation of, with s or s^2 , when data are grouped or rounded, 187, 188, 201
definition of, 12, 43, 100, 192
as descriptive statistic, effect of grouping or rounding on, 187-188
design of experiments for testing, 17, 27*n.*, 28*n.*, 60-66, 81, 82, 377-382, 423
distribution of, for arbitrary population, 197, 198
effect of grouping or rounding on, 186-198, 203
for normal population, 162
effect of grouping or rounding on, 187, 188, 196, 198, 212, 213
efficiency of, in normal samples, 162
when data are grouped or rounded, 197
as estimator of population mean (μ), arbitrary population, 197, 198
when data are grouped or rounded, 196-198, 212, 213
normal population, 162
(*See also* Confidence limits, for μ)
expected value of, 197, 198, 212
importance of distinguishing from population mean (μ), 12
mean of, 197, 198, 212
moments of, in samples from arbitrary, grouped, and normal populations, 197, 198
use in quality control, 34, 42-44, 147-150
in variables inspection for fraction defective, 9-14, 33, 34, 41-44, 48, 53, 56, 58-64, 71-73, 83-85
variance of, 162, 197, 198
yardsticks for, 150
Sample mean deviation (*see* Mean deviation)
Sample median (*see* Median)
Sample size, adjustment of, by modifying OC curve, 19
Sample size, average, 233, 236, 420, 427
(*See also* ASN curve)
changes of, effect on OC curve, 21, 45
for each of two samples (*see* N , second listing)
for single sample (*see* N , first listing)
(*See also* Amount of inspection; Computation of number of observations needed; Formula, for number of observations needed; N_a , N_m , N_i , N_d)
Sample standard deviation, 12, 13, 187*n.*, 188*n.*
(*See also* s)
Samples, combined, 42, 43
Sampling, biased, 160
curtailed, 14, 238, 361
random, role of, in experimentation, 158-160
representative, likelihood of bias of, 160
Sampling inspection, aims of, 156-158
control features of, 42, 43, 157
effectiveness of, 156-158
(*See also* Operating characteristics; Operating-characteristic curves; Operating-characteristic surface)
objectives of, 156-158
risks involved in, 228, 229
(*See also* Consumer's risk; Producer's risk)
steps in, 13, 14
value of, dependent upon quality of submitted product, 42
(*See also* Acceptance inspection; Inspection)
Sampling-inspection plans, attributes (*see* Attributes, inspection)
changes in, 41-45, 142-145
classification of, 237
comparison of, 26-28, 85, 237-244, 419, 420
double, 237-244
multiple, 237-244
multivariate, 111-184
sequential, 83-85, 232, 233, 358-362, 419-428
single sample, 7-82, 111-184, 231, 232, 237, 249-264, 269-296, 331-338, 377-381, 385-393
(*See also* Acceptance inspection; Inspection; Statistical tests)
Savage, Leonard J., ix, xii, 238*n.*, 244, 354, 364
Scale readings, 188, 189
Scheffé, Henry, 109
Schumpeter, Joseph A., 145*n.*, 183
Scores, examination, dispersion of, 280
use of, in acceptance inspection and quality control, when several quality characteristics are involved, 50-52, 113-116
Sealy, E. H., 156, 157, 184
quotation from, 156, 157
Semi-invariants, of rectangular distribution, 195, 196*n.*
Sheppard's corrections for, 196*n.*, 222
Sensitivity tests, 341, 342
analysis of data from, 342-345
optimum design of, 345, 346, 349-352
use of preliminary data in, 346-349
Sequential analysis, 26, 83-85, 232-234, 237-244, 357-362, 367-372, 417-429
advantages of, 26, 367-371, 419, 420

- Sequential analysis, compared with non-sequential analysis, 26, 85, 237-244, 367-372, 419, 420
 conditions for superiority of, over non-sequential analysis, 369, 371, 419, 420
 for superiority of non-sequential analysis, 371, 420
 definition of, 237, 367, 419
 disadvantages of, 371
 elements of, 417-429
- Sequential design, of experiment, for locating maximum of a function, 367-372
 when failure rate of equipment is high, 353-362
- Sequential estimation, of parameter of binomial distribution, reference to, 238n.
- Sequential-sampling-inspection plans, 83-85, 232, 233, 358-362, 421-426
 (See also Statistical tests, sequential)
 acceptance line, in graphical procedure for, 232, 356, 357, 359, 360, 422, 423, 425
 (See also Acceptance line)
 acceptance number in, 237, 422, 425
 amount of inspection in, (see Amount of inspection, with sequential sampling)
 operating-characteristic curves of (see Operating-characteristic curves)
 that provides for rejection only, 357-362
 rejection line, in graphical procedure, 232, 356, 357, 359, 360, 422, 423, 425
 (See also Rejection line)
 rejection number in, 237, 422, 425
- Severity of test, cannot be controlled precisely, inspection for fraction defective when, 331-338
- Sheppard, W. F., 188, 193, 196, 197, 199, 203, 223
- Sheppard's corrections, 193-196
 bivariate, references to, 193n.
 conditions for strict validity of, 193
 consequences when not fulfilled, 196
 implications of, 194
 conditions for validity "on the average," 194-196
 when grouping lattice is located at random, 194-196
- for J-shaped distributions, 194
 references to, 194n., 223
- multivariate, references to, 193n., 223
- not to be used, in computing confidence limits, 199, 200, 203
 in evaluating tests of significance, 199, 200, 203
- Shewhart, Walter A., 47n., 49n., 58n., 93, 97n., 110, 221n., 223
- Short cuts, in analysis of 2×2 table, 253-255
- σ : standard deviation of lot of population (see Standard deviation, of lot; of population)
- $\sigma(N)$: standard deviation of number of items inspected, 238
 figures showing, for double-, multiple-, and sequential-sampling plans, 241, 243
- σ_s : standard deviation corresponding to standard method, process, or product, 269
- σ_1 : standard deviation corresponding to new method, process, or product, 269
- σ_1 : standard deviation defining good quality, when lot quality is measured by fraction of sample ranges that exceed specified limit, 229-231
- σ_1 : standard deviation of the first of two methods, processes, or products, 280
- σ_2 : standard deviation defining bad quality, when lot quality is measured by fraction of sample ranges that exceed specified limit, 229-231
- σ_2 : standard deviation of the second of two methods, processes, or products, 280
- Significance, statistical tests of (see Statistical tests)
- Significance levels, of Bartlett's test, approximation to, 388
 tables of, reference to, 388n., 394
 of χ^2 , approximation to, 255
 tables of, reference to, 255
 of χ^2 , Cornish-Fisher type expansion for, reference to, 109
 for one degree of freedom, equivalent to K_{α}^2 , 258n.
 relation of, to partial sum of Poisson series, 109
 to significance levels of F-distribution, 316
 tables of, references to, 315n.
- of Cochran's test, tables of, 390, 391
- of F, Paulson's approximation to, 393, 394
 for $n_1 = \infty$, equivalent to significance levels of χ^2 , 316
 relation of, to percentage points of Fisher's s , 317n.
 of incomplete beta function, 392, 393
 tables of, comments on, 151n., 152n., 317n.
 references to, 151n., 184, 317n., 318
- Hotelling's T (see Significance levels, of T)
- meaning of, 270, 271, 281
- of normal distribution, relation of, to probits, 343
 short table of, 18
 tables of, references to, 10n., 18, 343n.
 need for care in using, 10n.
- of range, in samples of k from normal distribution, curves showing, 230
 table of, reference to, 229n., 234
- of T , asymptotic expansion for, 155
 relation of, to significance levels of χ^2 , 155
 of F , 155
- of t , asymptotic expansion for, 148, 149n., 184
 tables of, references to, 148n.
- of z , relation to significance levels of F , 317n.
- Significant differences (see Statistical tests)
- Significant figures, 189
 definition of, 189n.
 recording excessive number of, 191, 192
 too few, 192
- Simaika, J. B., 310n., 318
- Simon, Herbert A., 381, 382
- Simultaneity of events, acceptance inspection for, 227-234
 formulation in terms of σ , 229-231
 measured by fraction of sample ranges that are less than specified limit, 227, 228

- Single-sampling-inspection plans, 7-82, 111-184,
231, 232, 237, 249-264, 269-296, 331-338,
377-381, 395-393
(See also Statistical tests, single-sample)
acceptance number in, 237, 280n., 263, 264
amount of inspection (see Amount of inspection,
with single sample)
curtailment of, 14, 238
operating characteristics of (see Operating
characteristics; Operating-characteristic
curves; Operating-characteristic surface)
rejection number in, 237, 260n., 263-274
Skewness, of distribution of \bar{x} , when data are
grouped, 198
measures of ($\sqrt{\beta_1 \gamma_1}$), 197, 198
Slope, of linear regression function (β), 322
determination of, when cost of each measure-
ment depends upon its magnitude, 319-328
when dependent variable is expressed in
probits, 343, 350
references to, 343n., 352
relation of, to σ , 343
two-point estimate of, formula for, 350
Small samples, effect of grouping or rounding on
statistical analyses of, 203-215
efficiency of, as basis for decisions, 156, 157
Smith, B. Babington, 120n., 184
Snedecor, George W., 405, 415
Solomon, Herbert, ix, 384
Specifications, inconsistent, 50n., 51n.
redundant, 50n., 51n.
Sponsorship, vii
Square-root transformation, 411, 414
Stabilizing variance, by transformation of data,
408-414
Standard; new method, process, or product com-
pared with, with respect to fraction defective,
7-93, 27n., 28n., 231-234, 237-244, 270, 271,
274, 275, 278-280, 423
with respect to level of performance, 17, 27n.,
28n., 59-63, 81, 82, 423
with respect to variability of performance,
227-234, 270, 271, 274, 275, 278-280
(See also Old method)
Standard deviation, of binomial distribution, 255,
397
of correlation coefficient (see Variance)
of lot (σ), as measure of lot quality, 27n., 28n.,
229-231, 269-296
(See also Standard deviation, of population)
of mean (see Variance)
of mean deviation (see Variance)
of median (see Variance)
of normal distribution (σ), 9, 12, 58, 97, 161,
229, 342, 378, 423, 426
bias of s as estimator of, 58
adjustment factor, formula for, 58
tables of, references to, 58n.
as parameter of, 12, 161
as reciprocal of slope of regression line, when
dependent variable is expressed in probits,
343
of number of items inspected ($\sigma(N)$), 238
Standard deviation, of number of items inspected
($\sigma(N)$), figures showing, for double-, multi-
ple-, and sequential-sampling plans, 241, 243
of Poisson distribution (see Variance)
pooled estimate of, 43
of population (σ), bias of s as estimator of, in
normal samples, 58
confidence limits for (see Variance)
estimation of, from mean deviation, 162, 163,
169
from probit data, 342-352
from range, 227, 227n.
from s , in normal samples, 58
from sensitivity tests, 342-352
(See also Variance)
importance of distinguishing from s , 12
as parameter of normal distribution, 12, 161,
tests of significance relating to, sequential,
232, 233, 426
single-sample, 231, 232, 269-296, 365-394
of proportion or percentage, 255, 397
of r (see Variance)
of range, 227n.
of rectangular distribution, 218
of s , in normal samples, formula for, 58
of sample, 12, 13, 187n., 188n.
Standard error (see Standard deviation)
Standard method, process, or product, compared
with a new (see Old method)
Stanford University, ix, xi, xii, 96, 384
Statistical hypothesis, alternative, 419, 420
null, 420
under test, 419, 420
Statistical Research Group, iii, ix-xi, 6, 8n., 20n.,
28n., 31n., 42n., 52n., 83n., 85n., 93, 101n.,
108n., 109n., 143n., 184, 188, 231n., 234,
237n., 244, 257n., 260n., 335n., 358n., 361n.,
362, 400, 405n., 415, 419n., 420n., 428, 429
senior scientific staff of, list of names, ix, x
Statistical tests, analysis of variance, 312-314,
385, 386
for components of variance, 312-314
for homogeneity of means, 385, 386
Bartlett's, for homogeneity of variance esti-
mates, 183, 386-388
based on sign of difference between sample
means, 377-382
conditions rendering optimal, 381, 382
bias of, if Sheppard's corrections are used, 199,
200, 203
binomial distribution, based on, 249, 250, 255
for comparing parameters of two, 249-258,
424, 425
for testing parameter of a single, 260n., 263,
264, 421, 422
with provision for rejection only, 358
 x -test, 254-257
 χ^2 -test, for deciding from s_1^2 , whether $\sigma_1^2 > \sigma_0^2$,
270-278
for deciding from s_1^2 , whether $\sigma_1^2 < \sigma_0^2$,
278-280
for deciding from "sum of squares" whether
 $\sigma^2 > \sigma_1^2$, 231, 232
for homogeneity of proportions, 256, 257

- Statistical tests χ^2 -test, for homogeneity of proportions, of 2×2 table, 254, 255
of variance estimates, 386-388
Cochran's, for significance of largest variance estimate, 383-394
for comparing two binomial distributions, 249-258, 263, 264, 424, 425
two means, 61, 62
two percentages or proportions, 249-258, 263, 264, 424, 425
two standard-deviation or variance estimates, 280-297
for components of variance, 312-314
curtailed, 14, 238, 361
for determining whether new method, process, or product exceeds a standard, with respect to fraction defective, 7-93, 27n., 28n., 227-234, 237-244, 270, 271, 274, 275, 278-280, 421-423
with respect to level of performance, 17, 27n., 28n., 59-63, 81, 82
with respect to variability of performance, 227-234, 270, 271, 274, 275, 278-280
for determining whether a particular one of two methods, processes, or products exceeds the other, with respect to fraction defective, 249-258, 263, 264, 424, 425
with respect to level of performance, 59-63, 380
with respect to variability of performance, 280, 282, 283, 296
for difference of means, 59-63, 380
of percentages or proportions, 249-258, 263, 264, 424, 425
for double dichotomy, 249-258, 424, 425
double-sampling, for fraction defective, 237-244
effect of grouping or rounding on, with large samples, 191-203
with small samples, 203-215
errors of the first and second kinds associated with, 271, 281, 282
F-test, in analysis of variance, 311-314
for components of variance, 311-314
for homogeneity of means, 385-386
of ratio of standard deviation or variance estimates, 280-296
for four-fold table, 249-258, 424, 425
for fraction defective, based on enumeration data, 237-244, 249-258, 260n., 263, 264, 421, 422, 424, 425
based on measurements, 7-93, 27n., 28n., 227-234, 270, 271, 274, 275, 278-280, 423
general one-parameter, sequential, 426-428
single sample, 61, 62
generalized Student's *t* ratio (see Hotelling's *T*)
for generalized variance, reference to, 166
graphical, 34-37, 52-56, 66-71, 232, 233, 260, 356-359, 398, 414n., 416, 422, 423, 425
grouping, effect of, on, with large samples, 191-203
with small samples, 203, 215
for homogeneity, of means, 61, 62, 385, 386
of percentages or proportions, 249-258, 263, 264, 424, 425
Statistical tests, for homogeneity, of 2×2 table, 249-258
of variance estimates, 385-389
Hotelling's *T*, 114-116, 152-156
indifference value in, 282
for mean, comparison of two or more, 50-63, 380, 385, 386
test of a single, 61-63, 71-73, 83-85, 197, 198, 200-203, 212, 213, 423, 426
mechanical (see Fulcher-Zubin Item Analyzer)
multiple-sampling, for fraction defective, 237, 244
multivariate, 50-52, 114-116, 147-156
number of observations required (see *N*; \bar{N} ; N_0 ; N_m ; N_1 ; N_i)
(See also Amount of inspection; ASN curve; Computation of; Formulas)
omnibus, 386
one-decision sequential binomial test, 358
one-sided or one-tail, 52, 57, 150, 152, 156, 426
operating characteristics of (see Operating characteristics; Operating-characteristic curves; Operating-characteristic surface)
for order of population means, 377-382
planning (see Design of experiments)
for proportions or percentages, comparison of two, 249-258, 263, 264, 424, 425
test of a single, 237-244, 260n., 263, 264, 421, 422
with provision for rate of failure of equipment, 356-362
for range in samples of *k*, formulation in terms of sample "sum of squares," 220-231
for ratio of two standard-deviation or variance estimates, 280-296
risks associated with, 271, 281, 282
(See also Operating-characteristic curves)
sequential, 83-85, 232, 233, 358-362, 421-426
for sign of difference between population means, 377-382
significance levels of (see Significance levels)
for standard deviations or variances, comparison of two or more, 231-233, 269-296, 385-394, 428
T-test, Hotelling's, 113-116, 147-156
t, non-central, 71-73
Student's, 72, 147-149, 200-203, 214, 215
relation of, to Student's *z*-test, 200
two-sided or two-tail, 52-57, 150, 152, 156, 426
transformation of data in, 257-259, 261-264, 395-416
truncated, 14, 238, 361
for variance components, 312-314
for variances (see Statistical tests, for standard deviations)
Statistics, sample, contrasted with population parameters, 161
Steffensen, J. F., 221n., 223
Stigler, George J., ix
Student (William Sealy Gosset), 187, 200, 201, 203, 223
quotation from, 187, 188
Student's *t*, definition of, 72, 200

- Student's t , distribution of, effect of grouping or rounding on, with large samples, 200-203
with small samples, 187, 188, 214, 215
percentage points of, asymptotic expansions for, 148, 149n., 184
tables of, references to, 148n.
relation of, to Student's z , 200
Sheppard's corrections not to be used in computing, 203
- Student's z , definition of, 187n.
effect of grouping on, 187, 188 (*See also* Student's t)
relation of, to Student's t , 200
- Systematic variation, 310, 311
- T
- T : angular difference between two binomial probabilities P_x and P_a , 262, 264
- T : generic symbol for an estimator of a parameter θ , 408
- T : Hotelling's generalized Student ratio, definition of, 142, 154, 155
distribution of, 154, 155
asymptotic expansion for percentage points of, 155
free from nuisance parameters, 115
relation to χ^2 -distribution, 155
to F -distribution, 155
optimum properties of, 147
as "score," combining results of two or more tests, 113-116
- T : Zelen's symbol for a transformed proportion, 405, 415
- T -statistics, advantages of, 115, 164
applied to air testing of bombsights, 122-142, 164-168
control charts for, figures showing, 132, 134, 136
control limits for, computation of, 152-155
definitions of, and relationships, 131, 133, 153, 154
distributions of, 152-155, 164
uses of, 115
yardsticks for, computation of, 156
- t : angular difference between two observed proportions p_x and p_a , 264
- t : ratio of a normally distributed variable to an independent estimate of its standard deviation, 72, 73
(*See also* Student's t ; Non-central t)
- t_0 : Johnson and Welch notation for a given level of non-central t , 73
- Tables, checking of, x
list of principal reference, xiii
- Tabular entries or values, effect of further rounding of, 191
Fisher-Wishart recommendation regarding, 221
statistical properties of, 215-218, 221
- Tchebycheff inequality, 40, 221
- θ : angle corresponding to an observed proportion, 257, 258, 398, 400
- θ : generic symbol for a parameter of a probability distribution, 408, 426
- θ_0 : value of θ when null hypothesis is true, 426
- Thompson, Catherine M., 110, 151n., 152n., 184, 315-318, 333, 335n., 336n., 338, 388n., 393, 394
- Tightened inspection, 41-45
criterion for changing to, when lot quality is measured by fraction defective, 42
procedure for judging whether criterion is met, using variables data, 42-45
when upper and lower limits are imposed on a single quality characteristic, 56
effect of, on OC curve, 45
methods of achieving, with variables inspection for fraction defective, 45
purpose of, 41, 42
- Time to rupture, for test specimens, 321, 365
determination of, when cost of each measurement depends on its magnitude, 322-328
determination of composition yielding maximum, 365-372
- True trends, effect of, on statistical analyses, 371, 372
- Tippett, L. H. C., 120n., 184, 227n., 234
- Tolerance factor (K), for normal distribution, 97-108
definition of, 97, 98
formulas for, 101, 108
table of values of, 102-107
uses of, examples of, 100, 101
(*See also* Tolerance limits)
- Tolerance limits, statistical, 47, 97-108
conditions for satisfactory use of, 97
contrasted with confidence limits for population mean, 99, 100
definition of, one-sided, 47, 98, 99
two-sided, 97, 98
distribution-free, 99, 109
for non-normal distributions, 99, 109
for normal distributions, 47, 97-99, 100-108
one-sided, 47, 98, 99
computation of, example, 47
two-sided, 47n., 97-99, 100-108
examples of, 100, 101
factors for, table of, 102-107
formulas for, 101, 108
- Transformation, angular, 257-259, 261-264, 336, 395-416
general, to stabilize variance, 408-410
inverse hyperbolic tangent, 413
inverse sine, 257-259, 261-264, 336, 395-416
logarithmic, of F , 317n.
of r , 413
of s or s^2 , 413
probit, 343, 352
square root, 411, 414
 z , of correlation coefficient (r), 413
of variance ratio (F), 317n.
- Transformed correlation (ρ), 413
- Transformed percentage or proportion (ϕ, T, θ), 257, 258, 398, 400, 405, 415
(*See also* Inverse-sine transformation)
- Trends, effect of, on statistical analyses, 371, 372
- Tukey, John W., 109, 414n.

2 × 2 table (see Double dichotomy)

Two-sided criterion, in variables inspection for fraction defective, 52-57, 63, 64

Two-sided or two-tail tests, 52-57, 150, 152, 156, 420

Two-sided tolerance limits, 47n., 97-99, 100-108

U

U: normal deviate exceeded with probability p , 72

U: upper limit of acceptable ranges in sample of k , 227, 228

U: upper limit of a measured quality characteristic, above which an item is defective, 9-12 (See also L)

selection of, 46, 47

as tolerance limit, 47

U-shaped distribution, 194, 222

United States Government, vii

(See also Army; Bureau of the Census; Department of Agriculture; National Bureau of Standards; National Defense Research Committee; Navy; Office of Scientific Research and Development)

Universe (see Lot; Population)

University, Brown, ix

of Chicago, iii, ix-xii, 6, 248, 320, 340, 364, 418

Columbia, iii, vii, ix-xii

(See also Statistical Research Group)

of North Carolina, ix, xi, 112, 248

Princeton, ix

Stanford, ix, x, xi, 96, 384

of Wisconsin, ix, 354

Upper and lower limits (see Two-sided criterion; Two-sided tests; Two-sided tolerance limits)

V

Variables, inspection by, 7-93, 113-184, 227-234, 269-296, 377-382, 385-393, 423, 426

advantages of, 7-9

amount of inspection in (see N ; \bar{N} ; N_m ; N_s ; N_t)

(See also Amount of inspection)

conditions for advantageous use of, 9

curtailment of, 14, 15

disadvantages of, 8, 9

for fraction defective, 7-93

acceptance criteria in, 12, 14, 17, 33-41, 52-56, 67-71, 85

(See also Computation, of acceptance region; Formula, for acceptance criterion; Graphical procedure)

advantages of, 7-9

amount of inspection, 17, 21, 27, 28, 64-66, 81, 82, 85

(See also Amount of inspection; N ; \bar{N} ; N_m ; N_s ; N_t)

condition for advantageous use of, 9

contrasted with attributes inspection, 7-9, 26-28

criteria, use of pair of one-sided in, 53, 54

figure showing, 55

criterion, use of single two-sided, 52-57, 63, 64

Variables, inspection by, for fraction defective, criterion for changing to reduced or tightened inspection in, 42

formulas for (see Formula)

graphical procedure in (see Graphical procedure)

when inspection is costly, 9

when lot mean (μ) is known, 27n., 28n., 230-234, 270, 271, 274, 275, 278-280

when lot standard deviation (σ) is known, 27, 28, 61, 62, 423

operating characteristics of (see Operating characteristics; Operating-characteristic curves; Operating-characteristic surface)

plan of action, 14, 16-21, 33-41

choice of, 45-49

sequential, 53-85

single sample, 7-82

when upper and lower limits are imposed on a single quality characteristic, 52-57, 63, 64

for fraction of ranges in samples of k that exceed specified limit, 227-234

formulation in terms of σ , 229-231

multivariate, 113-184

operating characteristics of (see Operating characteristics; Operating-characteristic curves; Operating-characteristic surface)

for percent defective (see Variables, for fraction defective)

sequential-sampling, 83-85, 232, 233, 423, 426

single-sampling, 7-82, 113-184, 231, 232, 269-296, 377-382, 385-393

use of several acceptance criteria in, 50-56, 63, 64, 113, 114

Variability, determining whether new method, process, or product exceeds a standard in respect to, 227-234, 270, 271, 274, 275, 278-280

determining whether a particular one of two methods, processes, or products exceeds the other in respect to, 280, 282, 283, 296

measures of (see Mean deviation; Range; Standard deviation; Variance)

Variance, analysis of, 297, 310-314, 386, 386

(See also Analysis of variance)

of binomial distribution, 397, 410

components of, 269, 297, 310-314

due to grouping or rounding, 195, 218

of correlation coefficient (r), 413

definition of, 161, 195

estimates of, 12, 13, 43, 162, 198 (See also s^2)

χ^2 -test of, 231, 232, 270-280

F -tests of, 280-296, 311-314

homogeneity of, Bartlett's test for, 183, 387, 388

largest of several, Cochran's test for significance of, 383-394

experiments pertaining to, design and analysis of, 227-234, 269-318

of grouped distribution, 195

of interpolated value, 219-221

of lot (σ^2), as measure of lot quality (see Standard deviation, of lot)

(See also Variance, of population)

- Variance, of maximum likelihood estimator of mean of normal population, when data are grouped or rounded, 197
 of mean, 162, 198
 when data are grouped or rounded, 197, 198
 of mean deviation, in normal samples, 162, 163, 169
 of median, in normal samples, 162
 of normal distribution, 161, 198
 (See also Standard deviation, of normal distribution)
 bias of s^2 as estimator of, when data are grouped or rounded, 198-200, 203-214
 estimation of, from mean deviation, 162, 163, 169
 from probit data, 342-352
 from range, 227
 from s^2 , 12, 13, 43, 162, 198-200, 203-214
 from sensitivity tests, 342-352
 as parameter of, 12, 161
 tests of significance relating to, sequential, 232, 233, 426
 single-sample, 231, 232, 269-296, 383-394
 of Poisson distribution, 411
 of population (σ), bias of s^2 as estimator of, when data are grouped or rounded, 198-200, 203-214
 confidence limits for, 198-200, 213, 214
 estimation of, from mean deviation, 162, 163, 169
 from probit data, 342-352
 from range, 227
 from s^2 , 12, 13, 43, 162, 198-200, 203-214
 from sensitivity tests, 342-352
 importance of distinguishing from s^2 , 12
 tests of significance relating to, sequential, 232, 233, 426
 single-sample, 231, 232, 269-296, 383-394
 of proportion or percentage, 397, 410
 of r , 413
 of range (See Standard deviation, of range)
 ratio (See F)
 of rectangular distribution, 195-218
 of s^2 , in samples from arbitrary, grouped, and normal populations, 199
 from normal population, formula, 199, 412
 when data are grouped or rounded, formula, 199, 211
 stabilizing, by transformation of data, general procedure for, 408-410
 applications of, 410-413
 (See also Inverse-sine transformation)
- Wald, Abraham, ix, 62n., 83n., 99, 108n., 110, 143n., 147, 166n., 184, 419n., 429
- Wallis, W. Allen, iii, x-xii, 6, 167n., 184, 248, 418, 419n.
- Weaver, C. L., 318n.
- Weaver, Warren, v, vii, x
- Weights, use of, in fitting line by least squares, 343, 344
 when dependent variable is expressed in probits, 343, 344, 350
- Welch, B. L., 8n., 22, 49, 58n., 64, 72-74, 76, 77, 79n., 86, 93, 99, 381, 382
 quotation from paper by, with W. J. Jennett, 49-50
- Wilenski, H., 46n., 93, 255n., 265
- Wilks, Samuel S., 99, 110, 166n., 173, 174, 184
- Wishart, John, 218, 219n., 220n., 221, 222
- Wold, Herman, 193n., 196n., 223
- Wolfowitz, Jacob, x, xi, 52n., 108n., 110, 330
- Work sheets, for acceptance-region boundary, using two-sided criterion, 57
 for k , 77-79
 for OC curve, 32, 80
- WPA tables (See Mathematical Tables Project)
- Wright, Sewall, 298
- X
- x : a measurement of a variable quality characteristic, 12
- \bar{x} : arithmetic mean of sample measurements (See Sample mean)
- $\bar{x} + ks$, 12, 14, 33, 36, 47n., 50, 53, 59, 61, 62, 64, 66, 71, 83
 (See also Acceptance criterion, in variables inspection for fraction defective; Tolerance limits)
- bias of, as estimator of $\mu + ks$, in normal samples, 58
- expected or mean value of, in normal samples, 58
- standard deviation of, in normal samples, 58
- $\bar{x} - ks$, 13, 47n., 53
- $\bar{X} + Ks$, 98, 99, 102
 (See also Tolerance factor; Tolerance limits)
- \bar{x} : mean of a normal distribution, 164
- Y
- Yardsticks, for differences of means, 150
 for T -statistics, 156
 for variance estimates, 156
- Yates, Frank, 18n., 93, 120n., 148n., 151n., 152n., 183, 234, 255, 258n., 265, 315n., 317n., 318, 342n., 343n., 352, 398, 399n., 405, 407, 415
- Yates' correction of χ^2 for continuity, 254, 257
- Z
- z : a normally distributed variable, 61, 73
- z -transformation, of correlation coefficient (r), 413
 of variance ratio (F), 317n.
- Zubin, Joseph, 257, 258, 265, 398, 400
- Zubin-Fulcher Item Analyzer, 257, 258, 405, 415